Schools and Social Capital: Economic Segregation and Long-term Outcomes*

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Abstract

How does economic segregation in schools impact students' future college enrollment and employment? Using data from Texas, I find that the typical (median) lower-income student goes through schooling having almost 10 times fewer upper-income classmates than their wealthier peers. This low exposure to upper-income classmates is mainly driven by residential and school socioeconomic segregation, not classroom assignment. To capture the impact of having more peers with higher family income I use within-school, between cohorts, variation in the proportion of upper-income students, controlling for school trends. Lower-income students in cohorts with a higher share of upper-income students are more likely to enroll in 4-year college and earn higher wages in early adulthood. These (small) positive impacts do not seem to operate through spillovers from peer academic achievement or changes students' in access to school resources. Further, I find that increasing exposure to lower-income students has no detectable impact on upper-income students' wages in early adulthood, suggesting that improving cross-income exposure may be non-zero sum.

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1 Introduction

An important goal of education is economic mobility, but the likelihood of a U.S. child earning more than their parents has declined in recent decades (Chetty et al., 2017). One factor long theorized to relate to economic mobility is social capital, defined as relationships with others that enable individuals to access resources (Bourdieu, 1986; Coleman, 1988).[1] Most recently, Chetty et al. (2022) revealed that friendships with higher-income individuals (cross-income social capital) account for a substantial portion of the variation in economic mobility across neighborhoods.

However, it remains unclear how the way schools are organized may hinder/enable cross-income friendships and why cross-income friendships might matter for economic mobility. The literature on school socioeconomic segregation suggests that cross-income exposure is not common (Owens, Reardon and Jencks, 2016; Dalane and Marcottee, 2022; Kalogrides and Loeb, 2013). Having more upper-income classmates could impact a lower-income student's future prospects by granting her access to resources (e.g., teacher quality and school spending) and/or facilitating peer interactions and access to more valuable social networks. Understanding what shapes cross-income exposure and why cross-income exposure might matter for economic mobility has important policy implications. For example, if the relationship between exposure to upper-income peers and economic mobility operates exclusively through access to school resources, then policies that equalize access to school resources may improve economic mobility without addressing school economic segregation.

To illuminate how economic segregation in k-12 schools impacts lower-income students' college enrollment and employment prospects, I document the contribution of district, school and classroom economic segregation on lower-income students' exposure to upper-income peers and the impact of upper-income peers on college enrollment and employment. I do this in two steps. First, using data from Texas I present descriptive facts on lower-income students' proportion of upper-income classmates between grades 5 and 12. I quantify the role of districts, schools and classrooms in accounting for differences in exposure to upper-income peers. I then capture how exposure to upper-income peers relates to friendship formation using the Add Health data and Chetty et al. (2022) school-level cross-income friendship measures. The second part of the paper estimates the relationship between exposure to upper-income students and students' college enrollment and employment. To identify the impact of having more upper-income peers, I use the within-school residual variation from school trend in the proportions of upper-income students. The residual cross-cohort variation in the proportion of upper-income peers is unlikely to impact students' access to school resources (as I show empirically) and so can capture if there are peer family income spillovers that are independent of access to

[1] Social capital theory has been applied in education and employment to identify the drivers of inequities (e.g., Bourdieu, 1986; Coleman, 1988; Fernandez and Fernandez-Mateo, 2006; De Giorgi, Pellizzari, and Redaelli, 2010; Schmutte, 2015).

school resources (e.g., passage of institutional knowledge). I also disentangle the role of peer family income from peer achievement by controlling for the share of higher achieving peers.

I draw two main conclusions: first, lower-income students are exposed to very few peers with higher family income (upper-income students). The gap in exposure to upper-income classmates between lower- and upper-income students is approximately double the gap in exposure to higher-achieving classmates—41 percentage points relative to 20 percentage points. Second, the positive peer income effect on lower-income students' college enrollment and employment does not seem to operate through peer achievement. Prior work on peer effects in k-12 has generally focused on peer academic achievement (see, e.g., Imberman et al, 2012; Lavy, Paserman and Schlosser, 2012; Jackson, 2013; Feld and Zoelitz, 2017).

To capture the likelihood that lower-income students are exposed to upper-income peers in their classrooms, I use Texas state administrative data from 2004 to 2022 in which I have information on the exact classrooms students are in and follow students from grades 5 to 12. I define exposure as the proportion of a student's cumulative number of classmates between grades 5 and 12 who are higher income (excluding the student herself). I use "higher/upper income" and "lower income" as shorthand for students who are always below the free/reduced lunch income eligibility cutoff (income below $51,338 for a family of four) and those who are always above the free/reduced lunch eligibility cutoff, respectively. Upper-income students constitute approximately 24% of students enrolled in public schools in Texas.[2] For comparability, I define higher-achieving students as those who scored in the top 24 percentiles of reading test scores in grade 4.[3]

On average, 10% of lower-income students' classmates are upper income over the period from grades 5 to 12 compared to 51% of upper-income students' classmates being upper-income. The distribution of exposure is right-skewed: the median lower-income students' proportion upper-income classmates is 6% and one in every five lower-income students goes through grades 5 to 12 with a share of upper-income classmates smaller than 1%.[4] Lower-income students are more likely to be exposed to higher-achieving students (students who scored in the top 24 percentiles of their grade 4 reading tests) than they are to be exposed to upper-income students. On average, 18% of lower-income students' classmates are high-achieving over the period from grades 5 to 12.[5]

[2]The income cutoffs described are based on free/reduced lunch income eligibility in 2022. This definition of economic disadvantage builds on Michelmore and Dynarski (2017), who find that the number of years on free/reduced lunch captures student economic disadvantage better than a binary measure of economic disadvantage based on one year of free/reduced lunch eligibility status. Among students for whom financial aid data are available, I find that those with lower and higher incomes have a median parental income of approximately $22,000 and $117,119, respectively.

[3]Test scores are based on standardized grade 4 TAKS (2007–2011) and STAAR (2012–2018) reading tests. I use grade 4 because it is prior to when I start following students in the data and documenting their cross-income and test-score exposure. The estimates are similar if I instead used their math test or their average standardized score between grades 3 and 8.

[4]Students on average have 2000 classmates between grades 5 and 12; i.e., 20% of lower-income students go through grades 5 to 12 interacting with fewer than 20 higher-income classmates. I equally weight every time a student shares a class with another student but the patterns are similar if I only count the first time a student interacts with a new upper-income classmate.

[5]The gap in exposure to higher-achieving students is consistent if instead achievement is based on average grades 3 to 8

The low exposure to upper-income students is mainly driven by residential and school socioeconomic segregation. Residential (district) segregation and school (within district) segregation each account for 71% and 23% of the difference between lower-income students' exposure to upper-income peers and the socioeconomic integration benchmark, respectively. For the average lower-income student, within-school classroom sorting by income does not matter much for exposure to upper-income students: had students been randomly assigned to classrooms, their exposure to upper-income students would have increased by only 0.7 percentage points. The relatively small contribution of classroom assignment suggests policies seeking to improve cross-income exposure should focus on residential and school segregation. However, the average contributing role of the classroom to exposure to upper-income students misses important student heterogeneity in the potential gains from classroom integration: at the 10th percentile of students' distribution of the contribution of classroom segregation, lower-income students would have been exposed to 4.2 percentage points more upper-income students had students been randomly assigned to classrooms. The relative importance of residential segregation is consistent with the findings of Owens, Reardon, and Jencks (2016), who report that approximately two-thirds of income segregation between schools is due to segregation between districts. However, Owens, Reardon, and Jencks (2016) did not have classroom level data and so were not able to quantify the role of the classroom.

Having established that lower-income students are exposed to few upper-income students, the question that follows is if exposure to upper-income students matters for students' long-term outcomes and if so, why? One way to identify if exposure to upper-income students matters is to examine if it correlates with Chetty et al. (2022) measure of the likelihood of cross-income friendships which strongly relates to economic mobility. To identify the relationship between exposure to upper-income peers and cross-income friendship measures, I link publicly available school-level data published by Chetty et al. (2022) on the likelihood of cross-income friendships based on Facebook data with school measures of cross-income exposure in Texas. I find that low-SES students' school average proportion of high-SES friends (school economic connectedness as captured by Chetty et al. (2022)) is highly correlated with lower-income students' school average proportion of upper-income classmates in Texas as shown in Figure 12: the correlation is approximately 0.9.[6] I also find that classroom assignment by income within schools in Texas is correlated with lower-income students' likelihood of befriending high-SES students conditional on school composition (school friending bias) as measured by Chetty et al. (2022): the correlation is approximately 0.6. The high correlation between within school sorting and friending bias suggests that school differences in cross-income friendships may in part be explained by differences in students' classroom assignment by income.

reading scores or math test scores.

[6]The economic connectedness measure is based on dividing the average proportion of high-SES friends by the the proportion of high-SES students in the population.

The question that follows is why might exposure to upper-income students matter for lower-income students' college enrollment and wages. I find that lower-income students with 10 percentage points more upper-income classmates also tend to have 3 percentage points fewer novice teachers.[7] The positive relationship between access to experienced teachers and the proportion of upper-income classmates suggests the relationship between cross-income exposure and long-term outcomes may be driven by differences in access to school resources. In other words it is not that lower-income students benefit from having more upper-income peers, it is that lower-income students benefit from having more experienced teachers who happen to be in upper-income classrooms. If it is driven by differential access to resources, then school equalization policies may be enough to address concerns with economic segregation.

To address selection concerns and try to isolate the role of peers independent of resources, I use within-school deviations from school trend in cohorts' proportion of upper-income students. The peer effects literature dating back to Hoxby (2001) has long used within-school variation in cohort composition to isolate the impact of changes in peer composition on student outcomes.[8] The identification strategy is based on the assumption that there are random variations between adjacent cohorts in the proportion of upper-income students that are independent of any cohort or school changes. In-line with this assumption, I find that deviations from the school trend in the proportion of upper-income students seem to be unrelated to lower-income students' demographic characteristics.

The temporary (small) changes in a cohort's proportion of upper-income peers in a school are less likely to impact students' access to school resources. Consistent with this, I find that residual variation in peer income has no impact on lower-income students' proportion of novice teachers, number of AP courses taken, and average school per-pupil spending.

Using cross-cohort deviations from school trend I find that a 10-percentage-point increase in the proportion of upper-income students increases lower-income students' enrollment in 4-year public colleges by 0.38 percentage points, quarterly wages at 22–25 by 1.7%, and income percentile rank by 0.33. The impact of the share of upper-income peers on lower-income students' college enrollment and wages is not sensitive to controlling for the share of higher achieving peers.[9] The consistent coefficient on the proportion of upper-income students suggests upper-income peer spillovers on lower-income students are independent of upper-income students' academic achievement. The positive impact on college enrollment appears to be driven by exposure to upper-income lower-achieving students.

[7] Even within a school, lower-income students with more upper-income classmates are less likely to have novice teachers.

[8] Since Hoxby (2000) this approach has been used extensively in the peer effects literature. For examples see Feld and Zölitz (2017), Lavy and Schlosser (2011) and Angrist and Lang (2004).

[9] The coefficient on the proportion of upper-income students is slightly larger when controlling for peer achievement.

The positive (marginal) impact of exposure to upper-income peers on lower-income students suggests that at least some of the gains to improving cross-income exposure do not operate exclusively through changes in access to (observable) school resources. As such, resource equalization policies may not be enough to address the harms of economic segregation. To address economic segregation we would want to swap upper- and lower-income students to improve lower-income students' exposure to upper-income peers. This would require upper-income students to be exposed to more lower-income students. I find that a 10 p.p. increase in the proportion upper-income students (holding constant the proportion of middle-income students, i.e. swapping lower-income students with upper-income students) would increase lower-income students' wages in early adulthood by 2.1% (p =0.02). Alternatively, a 10 p.p. increase in the proportion lower-income students (holding constant the proportion of middle-income students) has no detectable impact on upper-income students wages (-0.6% (p =0.5)). The lack of detectable effect on upper-income students suggests that increasing exposure to upper-income students may be a win-win/neutral situation for lower- and upper-income students.

This paper contributes to several literatures. First, it contributes to the segregation literature. This literature has focused primarily on racial/ethnic segregation (e.g., Clotfelter, Ladd, and Vigdor, 2002; Clotfelter, Ladd, Clifton and Turaeva, 2021) and academic sorting within schools (e.g., Antonovics, Black, Cullen, and Meiselman, 2022; Lucas and Berends, 2002). I study the contribution of segregation to cross-income exposure and how it relates to long-term outcomes. The school segregation literature is subject to multiple data limitations that hamper researchers' ability to document the effects of segregation on exposure and long-term outcomes, including a lack of observations on students within a classroom and/or on their college enrollment and employment outcomes (Owens, Reardon and Jencks, 2016; Dalane and Marcottee, 2022; Kalogrides and Loeb, 2013). Using rich administrative data from Texas, I can follow k-12 students over time through early adulthood, observe their classroom enrollment and peers, and link their classroom peer composition to long-term outcomes. Second, my work contributes to the literature on social capital and economic mobility. I build on the work of Chetty et al. (2022) on the relationship between cross-income friendships and long-term outcomes by identifying the source of the variation in exposure to upper-income peers and disentangling the impact of peer income from the effects of peer test scores and access to school resources.

Third, this paper relates to the large peer effects literature examining the relationship between peer composition and short- and long-term outcomes (examples include Sacerdote, 2001, 2011; Zimmerman, 2003; Lavy, Paserman and Schlosser, 2011; Black, Devereux and Salvanes, 2013; Cools, Fernandez and Patacchini, 2019; Zimmerman, 2019; and Rao, 2019). It is most closely related to the paper by Cattan, Salvanes and

Tominey (2022), which investigates the impact of exposure to the children of parents who attended elite schools in Norway. They find that exposure to elite peers increases enrollment in selective universities. I focus on the impact of exposure to upper-income students (regardless of parental education) on teacher quality, advanced coursework, college enrollment, and wages. Importantly, I examine whether the impact on college enrollment and wages is driven by having more upper-income peers, independent of their academic achievement and/or access to school resources.

The paper is organized as follows. In Section 2, I begin by laying out the theoretical framework of the analysis. Section 3 defines my measures of cross-income exposure and data used. Section 4 reports estimates of cross-income exposure at the state level and how they compare to cross-test score exposure, as well as district, school and classroom integration benchmarks. Section 5 describes the relationship between exposure to upper-income students and friendship formation. Section 6 reports the relationship between cross-income exposure and long-term student outcomes. Section 7 concludes the paper.

2 Conceptual Framework

Exposure to upper-income peers is a function of the district a student resides in, the school they enroll in, and the classroom they are assigned to or choose. At each of these levels, parents and students make decisions about where to live and what school and classroom to enroll in given their economic resources (household income) and subject to potential information imperfections and discriminatory barriers. These decisions and constraints shape not only their exposure to upper-income peers but also their access to neighborhood and school resources. The first part of the paper attempts to draw a complete picture of how each of these layers (district, school, and classroom) contributes to lower-income students' exposure to upper-income peers across grades.

Theoretically, exposure to upper-income peers could shape lower-income students' long-term outcomes in at least two ways: resource allocation and/or social capital.[10] The distribution of students by income across and within schools could shape how financial and instructional resources are allocated (e.g., Owens and Candipan, 2019 and Kalogrides and Loeb, 2013). Owens and Candipan (2019) find that schools in upper-income neighborhoods tend to have higher spending per student and higher salaries for teachers. Unequal resource allocation can also take place within a school, between classrooms. Kalogrides and Loeb (2013) find that upper-income students tend to be assigned more experienced teachers than lower-income students

[10] Other potential channels include classroom spillover and class rank. For example, changes in peer income composition may impact a teacher's ability to target instruction by changing how homogeneous a classroom is. Changes in classroom peers may also impact a student's rank in the class, which may have implications for her aspirations and long-term outcomes (Cattan, Salvanes, and Tominey, 2022).

in the same school.

Social capital has long been discussed as a type of capital that is independent of human and physical capital that may impact productivity (Coleman, 1988). Social capital is defined by the structure of relationships between individuals (Coleman, 1988). There are two potential channels through which social capital may impact students' long-term outcomes: information and norm setting (Coleman, 1988). An example of an information channel is if higher-income students are more likely to know which courses to take to improve their likelihood of being accepted into more selective colleges and that they are more likely to share this information with lower-income students when sharing the same classroom. Bourdieu (1986) suggests that individuals from upper-income households have higher cultural capital, which results in the persistence and reproduction of social structures. Cultural capital is defined as knowledge, skills, and tastes that are acquired because an individual belongs to a social class. The information channel is likely weaker the more information and skills are available to students through formal sources, for example through counselors.

The social norms channel depends on the prevalence (actual/assumed) of a behavior in a group. For example, if upper-income students are more likely to enroll in selective universities, this may create a norm/expectation that students apply and enroll in selective universities across income groups. Several papers have documented the potential importance of social norms on academic performance in schools, perceptions, and giving behavior (Frey and Meier 2004; Bursztyn and Jensen, 2015; Bursztyn, GonzÃ¡lez, and Yanagizawa-Drott, 2020).

The strength of the information and norm channels depends on the school and social structure. If upper- and lower-income students enrolled in the same school are likely to attend different classrooms (because of high sorting by income/test score), then they are less likely to pass on information and shape cross-group norms. It also depends on the strength of the cross-group relationships. If students are less likely to form friendships across income categories, then they may be less affected by cross-income exposure. Hoxby (2000) finds that peer achievement effects are stronger within a race. Michelman, Price and Zimmerman (2022) find that exposure to "high-status" students at Harvard in the 1920s and 1930s disproportionately improved access to elite social clubs for students who graduated from private schools. Similarly, Cattan, Salvanes, and Tominey (2022) find that the impact of having more classmates whose parents graduated from elite schools is stronger among high-SES students than among low-SES students. Section 6 examines whether and how changes in cohort composition impact the level of classroom sorting by income and interacts with student characteristics (student test scores and race/ethnicity).

The social capital channel may operate exclusively through students' academic achievement. In other words, it could be that upper-income students happen to perform better academically, and being around higher achieving students–independent of their income–has an impact on lower-income students' academic performance and labor outcomes. Some of the channels through which a higher proportion of higher achieving peers may impact student outcomes include: student class rank, teacher behavior and/or academic spillover through peer-to-peer tutoring. The peer effects literature suggests the impact of peer achievement may vary depending on students' own baseline academic performance (Cools, Fernández and Patacchini, 2019; Feld and Zölitz, 2017, Lavy, Paserman and Schlosser, 2011; Sacerdot, 2011).[11]

3 Data and Measures of Cross-Income Exposure

3.1 Data

I use longitudinal administrative data from the Texas Education Research Center (ERC) that link student data from the Texas Education Agency (TEA) to Texas Higher Education Coordination Board (THECB) and Texas Workforce Commission (TWC) data. These TEA data cover the period from 2004 to 2022 and include student test scores, courses (and class assignment starting in 2011), demographics, attendance, graduation, and assigned teachers (including teacher certification and demographics). My main measure of income is free/reduced lunch status. I use years of assignment to free/reduced lunch status to capture the degree of economic disadvantage.[12]

The college enrollment data (THECB) are from 2008 to 2022, but I focus on the 2014 to 2022 data. The THECB data comprise information on college applications to state public schools (including information on parental income and education status), as well as financial aid data, which also includes information on parental income. I focus on the following college enrollment outcomes: any college enrollment, 2-year public college enrollment, 4-year public college enrollment, highly selective college enrollment, and graduation from any college. Colleges are defined as selective if they are between levels 1 and 4 based on Barron's selectivity index (most to very competitive in 2009). The college data are limited to enrollments in the state of Texas.

The employment data (TWC) are from the years 2008 to 2022. These data include information on industry, employment level, and Quarterly wage. The employment data are based on unemployment insurance data and hence cover only employment in Texas. In Section 6, I use quarterly wage data from 2022. For each student, I capture the average quarterly wage from employment in the first three quarters of 2022. I use both the average quarterly wage and the percentile-ranked wage (ranked within cohort).

[11] Feld and Zölitz (2017) using random assignment to sections at university similarly find that peer academic achievement may negatively impact lower-achieving students.

[12] Test scores are mainly based on standardized grade 4 and 8 TAKS (2007–2011) and STAAR (2012–2018) reading and math tests.

To identify and better understand the link between exposure and friendship formation, in Section 5, I supplement the analysis with two other sources of data: Add Health data and publicly available high school measures of the likelihood of cross-income friendship based on Facebook data from Chetty et al. (2022), both of which I discuss in more detail in Section 5.

3.2 Measure of Family Income

To measure student income, ideally, I would have parental income for every enrolled student. In the absence of data on parental income, I use the proportion of years on free/reduced lunch to capture the degree of economic disadvantage.[13] I divide students into three main income groups: always, sometimes and never on free/reduced lunch.

The segmentation of students based on proportion of years on free/reduced lunch seems to capture the variation in parental income as shown in Figure 1. For students with financial aid data and who are never, sometimes and always in free/reduced lunch status, their average adjusted parental income is $141,686, $51,406, and $27,305, respectively.[14] I define upper-income students as those never in free/reduced lunch status. Upper-income students represent approximately 24% of the student population. Students sometimes and always in free/reduced lunch status constitute approximately 48% and 29% of the student population, respectively.

Using the proportion of years on free/reduced lunch seems to effectively capture the degree of economic disadvantage. Among students with financial aid data, I find that 59% of students who are always in free/reduced lunch status reported parental income that is below the federal poverty cutoff for a family of four.[15]

I test whether these patterns hold using other measures of income. For students who apply to public universities in Texas, I have additional information on parents' income bracket.[16] Of students who applied to public universities, 81% 24% and 3% who were never, sometimes and always on free/reduced lunch, respectively, report having parental income above $80,000.

For the rest of the paper, I refer to students who are never on free/reduced lunch as higher- or upper-

[13]To identify the proportion of years on free/reduced lunch, I use all years from 2004 to 2022.

[14]Median parental income is $117,119, $39,145 and $22,000, respectively. Students with financial aid data are a select, systematically different, group. Therefore, these averages are not representative of the average income for each of the groups. It provides us with a general sense of the variation and is likely an upper bound for students who are always on free/reduced lunch. Financial aid data are available for 52%, 35% and 30% of students who are never, sometimes, and always in free/reduced lunch status, respectively.

[15]Based on reported federal poverty cutoffs for 2020 to 2022.

[16]I have this information for 33% of students who are never on free/reduced lunch and only 18% and 14% of students who are sometimes and always on free/reduced lunch.

income. I refer to students who are sometimes and always on free/reduced lunch as middle- and lower-income students, respectively. This paper focuses on higher- and lower-income students.

3.3 Measure of Cross-Income Exposure

I define cross-income exposure as the proportion of classmates of another income group in a student's classroom. I focus on the proportion of upper-income students. I capture the cumulative exposure to upper-income students by following three cohorts of students (2012–2014) starting from fifth to expected twelfth grade in Texas. In each year, I capture the number of classmates in a student's classroom (excluding self). I also capture the number of upper-income classmates in the classroom (excluding own status). I divide the total number of upper-income peers student i encountered in all the classrooms they were enrolled in between grades five and twelve ($N^H_{(-i)}$) by the total number of peers student i encountered in those classrooms ($N_{(-i)}$): $\frac{N^H_{(-i)}}{N_{(-i)}}$.

One can understand this measure as capturing the proportion of potential interactions rather than the proportion of students. If a student is in multiple classrooms with the same student, the latter is included in the denominator (total student interactions) multiple times. She would also be included in the numerator if she were of upper income multiple times. The assumption is that what matters is the proportion of interactions rather than the proportion of students. Each interaction is likely to yield an additional benefit. I assume that each interaction has an equal level of benefit.[17]

4 How Likely is Cross-Income Exposure and What is the Contribution of District, School and Classroom Economic Segregation?

4.1 Sample

To answer this question, I follow three cohorts of students from grade 5 to expected grade 12. The three cohorts are the 2012, 2013 and 2014 cohorts. Students enrolled in any public school (including charter schools) in Texas in grade 5 in academic year 2012 belong to the 2012 cohort. These cohorts of students are followed in the data, and their classroom income composition is documented every year from 2012 to 2019.

[17] Students may be in different classrooms with the same student. The second time they are with the same student, the gain from exposure to that student may be nonlinear. Similarly, the time spent with students in the same classroom can influence the amount of gain they would reap from that classroom exposure. For a random sample of 3000 students (1000 from each cohort) I compare their average exposure based on equal weighting of each interaction compared to weighting only the first interaction (weight= 1) and all following interactions with the same student are given a weight of 0. The patterns of exposure are very similar independent of weighting method.

Across these cohorts, there are 1,128,554 students. Table 1 summarizes the characteristics of the sample. Approximately 50% of the cohort identify as Latin-American students, 14% as Black students, and 68% as White students. Most of the students are enrolled in traditional public schools—4–6%, in a given grade, are enrolled in a charter school, as shown in Table 10.5. Table 10.5 summarizes the enrollment patterns of the students in each expected grade. Note that "expected" grade is not their actual grade but the grade in which we expect them to be enrolled given the year and their cohort.

4.2 Main Patterns of Exposure to Upper-Income Students

I find that the average lower-income student goes through grades five to twelve with 10% of their classmates are upper-income compared to 51% of upper-income students' classmates are upper-income as shown in Figure 2.[18] The distribution of exposure to upper-income peers is skewed to the right for low-income students, as shown in Figure 7 Panel (a). A large proportion of students are exposed to a small number of upper-income students. The typical (median) lower-income student is in classrooms with 6% upper-income students and for one in every five lower-income students 1% of their classmates are upper income.[19] The median lower-income student goes through grades 5 to 12 having met 39 upper-income students out of around 700 students, compared to 325 upper-income students for the median upper-income student.[20]

A concern we might have is that the low exposure to upper-income students is driven by differences across schools in how well they assign students to free/reduced lunch status. To address this concern, I also present students' exposure to upper-income students where upper-income is defined as the proportion of a student's total classmates who have financial aid data whose parental income is in the top 24 percentiles of the distribution of parental income reported in the financial aid data. The patterns of exposure to upper-income students are similar under this definition, though the gap is slightly smaller; Lower-income students go through grades 5 to 12 with 13% of their classmates with financial aid data have reported parental income in in the top 24 percentiles, compared to 43% of upper-income students' classmates. These patterns are shown in Figure A1.[21] The similar gap in exposure when using financial aid data suggests that the patterns

[18]If we instead segment students by years on free/reduced price lunch, we see that exposure to upper-income peers decreases as the number of years in free/reduced price lunch status increases as shown in Figure A2.

[19]On average, students during this period encounter 2000 classmates. Some may be repeated classmates in different classrooms.

[20]This statistic is based on a random sample of 3000 students (1000 from each cohort) for whom I only weighted their first interaction (first classroom shared) with an upper-income student and give a weight of 0 to every other interaction (classroom shared) with that same upper-income student. The difference in exposure between upper- and lower-income students based on weighting only the first interaction is slightly smaller (39 p.p.) compared to equally weighting each interaction (42 p.p.).

[21]The financial aid data may underestimate the gap in exposure because of left and right-tale missing data. If lower-income students are more likely to be in school with students who are lower in the parental income distribution who would not appear in the denominator of total classmates with financial aid data, the financial aid data would overestimate lower-income students' exposure to higher-income students. If upper-income students are more likely to be in schools with students who are higher in the parental income distribution who would not appear in the numerator of total classmates who are higher-income, the financial aid data would underestimate upper-income students' exposure to higher-income students.

we observe using proportion of years on free/reduced lunch status are capturing real differences between students in exposure to students with higher parental income.[22]

The difference in exposure to upper-income students is a function of residential, school, and classroom socioeconomic segregation. To identify how each of residential economic segregation, school segregation and classroom assignment contribute to exposure to upper-income peers I compare students' exposure to upper-income students to three benchmarks. In the first benchmark, students enrolled in the state are randomly assigned to districts, schools, and classrooms (district integration benchmark). In the second, the district composition is fixed, and students are randomly assigned to schools and classrooms (school integration benchmark). In the third, the school composition is fixed, and students are randomly assigned to classrooms (classroom integration benchmark). In practice, this is very similar to comparing lower-income students' average exposure to upper-income students to the proportion of upper-income students in the state, district and school. For example, if we were to randomly assign students across districts, the expected exposure to higher-income students would be equal to the proportion of higher-income students enrolled in the state of Texas.[23]

I show these benchmarks in Figure 2 with students' actual exposure to upper-income classmates. The difference between actual exposure and the district benchmark for full integration is 11.6 percentage points. In other words, had students been randomly assigned to districts, lower-income students would have been in classrooms with 11.6 percentage points more upper income classmates—that is more than twice lower-income students' current exposure. The difference between actual exposure and the school benchmark for full integration is 3.4 percentage points, and the difference between actual exposure and the classroom benchmark for full integration is 0.7 percentage points.[24] The relatively large difference between the district and school integration benchmarks is consistent with the findings of Owens, Reardon, and Jencks (2016), who report that approximately two-thirds of income segregation between schools is due to segregation between districts. However, Owens, Reardon, and Jencks (2016) did not have classroom level data and so were not able to quantify the role of the classroom.

[22] Classmates' average parental income based on financial aid data is $47,152 and $108,859 on average, for lower- and upper-income students, respectively.

[23] Since I am excluding own status, the expected exposure for higher- and lower-income students under random assignment will be slightly different; higher-income students would be exposed to fewer higher-income peers since their own status is not included in the numerator. This matters more in small units such as school classrooms. In each year, I calculate the benchmarks based on the number of students in the defined cohort still enrolled in a public school that year, as well as any students that share a classroom with a student in the cohort. This is particularly important in high school, where students may be enrolled in classrooms with students in other cohorts, and so their potential exposure may be different. I present my calculation of expected exposure under random assignment—excluding students' own status—in Appendix (A).

[24] The difference between actual exposure and the classroom integration benchmark can be explained by students taking different courses and/or students taking the same course but enrolling in different classrooms. In Figure A11, I add an additional benchmark: expected exposure in school course to upper-income students under random assignment to classrooms and label it "random class in course".I find that most of the difference between actual exposure and the classroom exposure benchmark can be explained by students taking the same course, enrolling in different classrooms.

The small difference between actual exposure and the classroom integration benchmark suggests that, for the average lower-income student, classroom assignment accounts for a very small portion of the low exposure to upper-income students. However, school classroom-level policies may be easier to implement, and popular district-level policies such as the addition of charter schools appear to have an even smaller impact on cross-group exposure.[25] The average contributing role of the classroom to exposure to upper-income students also misses important student heterogeneity in the potential gains from classroom integration: at the 10th percentile of students' distribution of gaps between the classroom integration benchmark and observed exposure, lower-income students would have been exposed to 4.2 percentage points more upper-income students had students been randomly assigned to classrooms. I find that 67% of lower-income students, compared to 30% of upper-income students, are exposed to fewer upper-income students than would be expected had students been randomly assigned to classrooms. In other words, a school's proportion of upper-income students overestimates lower-income students' exposure to upper-income students, on average.

The large contribution of residential and school socioeconomic segregation on students' exposure to upper-income peers would prompt us to think of policies that focused on greater district and school integration (e.g., racial integration policies such as Metropolitan Council for Educational Opportunity (METCO)'s voluntary busing program in Boston and race-based busing in Charlotte-Mecklenburg schools).[26] However, district (or school) integration policies may prompt districts (or schools) to track students by income into different schools (or classrooms).

To capture how the role of school and classroom sorting may vary by district composition, I split districts into percentiles based on the proportion of higher-income students in the district. Then, I present the average exposure of lower-income students to upper-income students in each district percentile and how it compares to the school and classroom full-integration benchmarks. Figure 4 captures the percentage point difference between the exposure of students to upper-income classmates and the school and classroom integration benchmarks. The school integration benchmark is captured by the height of the navy bar, and the classroom integration benchmark is captured by the height of the gray bar. The exposure of students to upper-income students in each percentile is captured by the height of the light blue bar.

I find that districts that are more integrated do not fully capture the benefit of having a higher proportion of upper-income students. The difference in exposure to upper-income students between the school and

[25] Monarrez, Kisida, and Chingos (2022) find that a charter school opening decreases the exposure of Black and Hispanic students to White and Asian students by approximately 0.3 and 0.1 percentage points, respectively.

[26] Setren (2024) finds that METCO improved bussed minority students' test scores and college enrollment and that bussed students were tracked in receiving schools to lower-performing classes. Bergman (2018) finds that a lottery-based (voluntary) desegregation program had a mixed impact on participating minority students who received offers to attend schools serving high-income, predominately white students; participating students were both more likely to enroll in college and be arrested for nonviolent offenses. Billings, Deming, and Rockoff (2014) find that the end of race-based busing widened racial gaps.

classroom benchmarks for integration and actual exposure are 13 and 2.6 percentage points in higher-income districts (districts enrolling 30% or more upper-income students), respectively.[27] The importance of classroom integration, particularly in higher-income districts, becomes increasingly important in high school as shown in Figure A12.[28]

The gaps in exposure to upper-income students may be driven by students in densely populated urban districts. As such, I also show the rate of exposure to upper-income students by district type based on NCES categorization: city, suburb, rural and town. Lower-income students living in cities are exposed to the smallest proportion of upper-income students (8%) and lower-income students in rural districts are exposed to the highest proportion of upper-income students (16%) as shown in Figure 3. The gap in exposure to upper-income students between upper- and lower-income students is largest in suburbs at 45 percentage points and smallest in towns at 17 percentage points.

If race and ethnicity are highly correlated with income, in practice, what appears to us to be socioeconomic segregation may actually be capturing racial/ethnic segregation.[29] To disentangle cross-racial/ethnic from cross-income exposure, I first present exposure to upper-income students by student race/ethnicity. Then, I capture exposure to same-race/ethnicity upper-income classmates. Lower-income students in all racial/ethnic groups are exposed to fewer upper-income students than their upper-income counterparts as shown in Figure 5.[30] The difference in exposure to upper-income classmates is smaller within racial/ethnic groups, suggesting that part, but not all, of the difference in exposure is a function of racial/ethnic segregation as shown in Figure A5. For Hispanic students, 28% and 4% of upper- and lower-income students' Hispanic classmates are upper-income. For Black students, 28% and 7% of upper- and lower-income students' Black classmates are upper income. For White students, 66% and 32% of upper- and lower-income students' White classmates are upper income.[31]

[27] The increasing gap between actual exposure and the school and classroom benchmarks is partly mechanical. There is more potential for sorting as the proportion of higher-income students increases. Although part of this may be mechanical, schools/districts with a higher proportion of higher-income students also have the highest potential to expose lower-income students to more upper-income peers, and the gap in exposure captures that missed potential. Of lower-income students, 12% reside in districts containing 30 percent or more upper-income students.

[28] Sorting across courses by income becomes increasingly important in high school, as shown in Figure A12. In grade 9 half of the difference between actual exposure and the classroom integration benchmark is driven by upper- and lower-income students taking different courses. The increasing importance of classrooms in older grades is consistent with Clotfelter, Ladd, Clifton and Turaeva (2021), who find that within-school segregation by race/ethnicity accounts for a larger portion of total segregation in high school.

[29] As shown in Figure A4, upper-income students account for only 9% and 11% of Hispanic and Black students, respectively, while they constitute the majority of White students (51%).

[30] White students across incomes are exposed to approximately 10 percentage points more upper-income classmates.

[31] The low exposure of Hispanic and Black, lower-income students to upper-income classmates of the same race/ethnicity is concerning if peer effects are stronger within racial groups. Students who share multiple characteristics may be more likely to befriend one another (Moody, 2001; Tuma and Hallinan, 1979). Hoxby (2000) finds that peer achievement has a stronger impact on students' test scores within races.

4.3 Exposure to Upper-Income Students Compared to Exposure to Higher-Achieving Students

The difference in exposure to upper-income students may capture differences in exposure to higher-performing students. Understanding how the relationship between exposure to upper-income students compares to exposure to higher-achieving students has practical and policy implications. If exposure to upper-income students is analogous to exposure to higher-achieving students, then it would be difficult to disentangle the spillover from having upper-income peers from having higher-achieving peers, and income desegregation policies may address both gaps in exposure to upper-income and higher-achieving students. If instead peer income and achievement compositions capture two different phenomena, then we could identify the impact of each on students' long-term outcomes separately, and interventions that address gaps in peer achievement would be different from those that address gaps in peer income.

I identify how exposure to upper-income students compares to exposure to higher-achieving students. Higher-achieving students are defined as students who scored in the top 24 percentiles of reading test scores in grade 4. Then, I follow students from grade 5 to grade 12 and document their exposure to higher-achieving students (instead of upper-income students). I chose the highest 24% of academic performance so that it is comparable to the proportion of students who are upper income (24% of students are upper income). I find similar patterns if I define higher-achieving students by their grade 4 math test scores.

The difference in exposure to higher-achieving students between upper- and lower-income students is considerably smaller than the difference in exposure to upper-income students. As shown in Figure 6, lower-income students are exposed to 20 percentage points fewer higher-achieving students than higher-income students. In comparison, the gap in exposure to upper-income students is closer to 41 percentage points.[32]

Students seem more clustered by income than by test score. The distribution of exposure to upper-income students is right-skewed, but exposure to higher-achieving students is normally distributed as shown in Figure 7 Panel (b): Lower-income students at the 25th percentile of the peer income distribution are exposed to 1.4% upper-income classmates. In comparison, lower-income students at the 25th percentile of the peer achievement distribution are exposed to 12% high-achieving classmates.[33]

[32] The gap in cross-test score exposure is also smaller than cross-income exposure as shown in Figure A8. Lower-achieving students are those who scored in the bottom 29 percentiles of their grade 4 reading test.

[33] I use grade 4 because it is prior to when I start following students in the data and more recent scores may be more predictive of long-term outcomes. That said, one test score may be subject to larger measurement error compared to the income measure which is based on multiple years of FRPL status. The size of the gap between upper- and lower-income students (at 23 p.p.) if I use grades 3 to 8 average test scores instead as shown in Figure A9. The distribution of exposure to higher-achieving students by student income is also is very similar if I use grades 3 to 8 average reading test scores instead—at the 25th percentile, lower-income students are exposed to 10% high-achieving classmates .

4.4 Variation in District and School Exposure to Upper-Income Students, Conditional on Student Income Composition

Low exposure to upper-income students is a function of both who enrolls in a district/school and how districts and schools are organized. Two districts (or schools) could have the same proportion of upper-income students, but in one district (or school) lower-income students are exposed to fewer upper-income students because they attend different schools (or classrooms).

I use the variance ratio to capture the exposure gap conditional on the proportion of upper-income students served in a school or district. Unlike the exposure measure, the variance ratio accounts for the change in the range of the potential gap between actual and expected exposure under random assignment by dividing the numerator by the range of potential exposure as shown in Equation (6) in Appendix B, where the variance ratio is discussed in more detail. In Figures 8 and 9, I plot the exposure of lower-income students to upper-income students in the district (or school) against the proportion of higher-income students in the district (or school).

In districts in particular, we can see that there is substantial variation in lower-income students' exposure to upper-income students among districts with similar compositions of students, which is explained by differences between school sorting levels. In districts with high levels of between-school sorting (top 20th percentile), lower-income students are exposed to 6.8 percentage points fewer upper-income classmates than the district average.[34] A factor that could explain differences in exposure to upper-income students, conditional on district income composition, is the number and type of schools offered. I find that districts with more charter and private schools relative to the number of students served tend to have higher levels of between-school sorting by income, as shown in Figure 10. Refer to Appendix C for more details on the method and findings.

In schools, school composition is highly predictive of the exposure of lower-income students to upper-income peers, but there is still some difference in the likelihood of being exposed to upper-income students, captured by the variation in the level of within-school sorting. In schools with high levels of within-school sorting (top 20th percentile), lower-income students are exposed to 2.5 percentage points fewer upper-income classmates than the school average. I find that the within-school sorting by income (variance ratio) declines by approximately 1.5 percentage points, from 11.5 to 10, when I control for students' grade 8 test scores and

[34] I map out districts' between- and within-school sorting rates in Figure A17. I also show the average difference between observed and school and classroom integration benchmarks in Figure A16. There are several districts in the west of Texas that have relatively large gaps in exposure to upper-income students and a lower proportion of upper-income students. There are also areas in the south of Texas where a high proportion of upper-income students reside, and the gap in cross-income exposure is smaller.

another 0.6 percentage points when I add an indicator for whether the student has taken Algebra I by grade 8. This suggests that academic preparation explains part, but not all, of the difference in classroom sorting by income within schools.[35]

The number and type of courses offered in a school could impact how students are tracked by test score and income. I find that the number of science and math courses offered in a school correlates most strongly with classroom sorting by income, regardless of whether those courses are advanced. This is shown in Figure 11.[36] These patterns may reflect schools' tracking policies or other school and student characteristics that correlate with sorting by income. In other work, I examine the impact of the addition of an advanced course using variation in the timing of when an advanced course is added to a subject area. I find that the addition of an AP course increases exposure to upper-income students and it appears to be driven by an increase in the proportion of upper-income students who take an AP course in the subject area (Mallah, 2024).

5 How Does Cross-Income Exposure Relate to Friendship Formation?

Having documented the rate of exposure to upper-income students, a question that follows is if exposure to upper-income students (as captured in this paper) matters for lower-income students' long-term outcomes. One way to answer this question is to identify if the measure of exposure to upper-income students relates to another measure that has already been documented to strongly correlate with economic mobility—Chetty et al. (2022) cross-income friendships measure. In prior work Chetty et al. (2022) find that cross-income friendships are strongly related to prospects of economic mobility. Differences in patterns of cross-income friendships may be attributed to differences in exposure to upper-income peers in schools and classrooms. In this section, I examine whether and how school exposure to upper-income peers relates to the likelihood of forming cross-income friendships.

To identify how a school's cross-income exposure relates to its students' average likelihood of cross-income friendship as captured by Chetty et al. (2022), I link the Texas administrative data with public high school measures on "economic connectedness" captured by Chetty et al. (2022). Economic connectedness is defined by Chetty et al. (2022) as the proportion of high-SES friends among low-SES individuals on Facebook divided

[35] In Table 2 Model (4), I find that the variance ratio declines only slightly (by 0.08 percentage points) when I also control for student attendance and suspension records in expected grade 8, which suggests that these "behavioral" controls do not provide any additional information. This estimate is based on regressing an indicator for student income on a student's proportion of upper-income classmates in a school. I include school and cohort-year fixed effects so that the coefficient on student income captures the difference between the proportion of upper-income students in upper-income relative to other students' classrooms in the same school.

[36] I regress the level of within-school sorting by income (captured using the variance ratio) for high schools on the number of courses offered divided by the number of students enrolled in 2019. The variance ratio is standardized based on the distribution of within-school sorting in schools weighted by the number of students enrolled. Similarly, the ratio of courses to students is standardized based on the distribution of courses to students in the sample of high schools in 2019, weighted by the number of students enrolled.

by the share of high-SES individuals in the population.[37] For each high school, I create a measure of exposure with which I capture the average proportion of lower-income students' classmates that are upper income in 2012.[38]

The likelihood that a lower-income student is exposed to a upper-income classmate is highly predictive of a school's economic connectedness, as shown in Figure 12 Panel (a). The correlation between the average proportion of upper-income classmates among lower-income students (exposure) in a school and economic connectedness is between 0.86 and 0.93.[39] The correlation between economic connectedness and exposure is consistent with Chetty et al. (2022), who find that a 10-percentage-point increase in exposure to higher-income peers in schools increases the likelihood of befriending a higher-income student by 8.9 percentage points. The strong correlation between my measure of exposure to upper-income students and the rate of cross-income friendships (economic connectedness) as captured by Chetty et al. (2022) can be thought of as a validity check: both measures seem to be capturing the rate of cross-income interactions in a school.

Chetty et al. (2022) find that, conditional on a school's income composition, students in some schools have a lower likelihood of befriending higher-income students (higher friending bias).[40] It is not clear why that is. It could be that lower-income students are exposed to the same proportion of upper-income students in both schools, but teachers or student characteristics better enable cross-income friendships in one school and not the other. Alternatively, schools' friending bias may capture differences between schools in within-school sorting by income, i.e., conditional on a schools' income composition, lower-income students may be more likely to share a classroom with an upper-income student in one school than in another school. I find that the correlation between within-school sorting by income (as captured by the variance ratio) and friending bias is between 0.61 and 0.67 as shown in Figure 12 Panel (b). The high correlation between school classroom sorting by income and friending bias suggests that the friending bias measure is likely capturing differences in lower-income students classroom exposure to upper-income students, conditional on school income composition.

The analysis above suggests that cross-income exposure and friendship formation as measured by Chetty

[37]Since they define high-SES as having above-median income, the share of high-SES friends is divided by 0.5.

[38]I use students enrolled in high school in 2012 instead of 2019 because the friending bias measures are based on Facebook friendship networks for individuals 25–44 as of 2022. I was able to merge 1,132 schools in the Texas data with the high school friendship measures, that is, 51% of schools serving grades 9–12. Of the 1,132 schools, 981 have data on economic connectedness measures.

[39]The range is based on whether I use the economic connectedness measure based on students' own income or students' parental income. The correlation between economic connectedness and exposure to upper-income students is approximately the same if I define exposure as the school average lower-income students' proportion of upper-income classmates or the school's proportion of upper-income students (independent of classroom). The similar correlation is likely because, as demonstrated in Section 4.2, classrooms contribute very little to lower-income students' average exposure to upper-income students.

[40]Friending bias is calculated as one minus the share of friends who are high SES divided by the share of individuals in the group who have high SES. If friendships are formed at random (i.e., high- and low-SES individuals have the same likelihood of befriending high-SES individuals), then friending bias would be equal to 0. Refer to Chetty et al. (2022) for more details.

et al. (2022) are strongly correlated at the school level. That said, it is not clear how predictive exposure to upper-income students is of individual students' likelihood of forming (close) friendships with upper-income students. To identify the relationship between exposure to upper-income students and individual students' (close) cross-income friendships, I use the Add Health data. The Add Health data contain information on individual student friendship patterns and enrollment in extracurricular activities. The in-school survey asks students to list up to five male and five female friends. However, they lack information on which classrooms students are enrolled in, and as such, I use it to capture the relationship between school (and extracurricular activities) peer income composition and friendship formation. Table A1 summarizes the demographics of students in Add Health.[41]

To capture the relationship between school (and extracurricular activities) peer income composition and friendship formation, I calculate the proportion of each student's listed friends who are high SES in the Add Health data. I define high-SES students as those in the top 24 percentiles of predicted income.[42] Then, I calculate the proportion of a school's student population that is high-SES and the proportion of a student's peers in extracurricular activities that are high-SES (excluding herself). Last, I run a regression with the proportion of high-SES peers in school (and another with the proportion of high-SES peers in extracurriculars) on the student's proportion of high-SES friends.

I find that for low-SES students, both the school and extracurricular income compositions are correlated with the proportion of high-SES friends: correlations of 0.37 and 0.40, respectively.[43] The relationship between exposure to high-SES students and friendship formation is presented in Figure 13. The fitted line is below the 45 degree line, suggesting that the composition of the school and extracurriculars does not perfectly predict the average difference in the proportion of high-SES peers (it is not 1-to-1) for low-SES students, but it comes close: For low-SES students, the slope between school composition and the proportion of high-SES friends is 0.78, and the slope between extracurriculars and the proportion of high-SES friends is 0.71.[44]

[41] I used the first wave of surveys from 1994 to 1995 that included in-school data for a sample of 85,627 students in 142 schools. I have information on friends and their SES for 77% of the students surveyed in school. For more information on how the Add Health survey was collected, see Harris et al. (2019)).

[42] I use student's predicted household income instead of actual household income because I only have information on household income for a subset of students surveyed. The Socioeconomic (SES) measure is based on the following variables used to predict household income: Father and Mother's occupation, Father and Mother's education, Father and Mother's employment status, number of individuals in the household, and missing indicators. Refer to Appendix D for a longer discussion of how I define high-SES students using the Add Health data.

[43] Note that students who enroll in extracurricular activities are likely a select group. Among low-SES students with extracurricular activities, the correlation between school composition and friendship formation is slightly stronger at 0.40. The stronger correlation in the Texas–Chetty et al. (2022) data compared to the Add Health data suggests that lower-income students' exposure to upper-income students is better at capturing differences in school average friendship patterns as measured by Chetty et. al (2022) based on Facebook data than it is at capturing differences in individual students' close friendship patterns as captured in the Add Health data.

[44] Low-SES students who enroll in extracurricular activities have four percentage points more high-SES friends than those who do not in the same school and grade. This might reflect the fact that low-SES students with more high-SES friends are more likely to enroll in extracurricular activities or that extracurricular activities provide the opportunity for friendships with

6 How Does Cross-Income Exposure Relate to College Enrollment, Graduation and Employment?

Having established that exposure to upper-income peers relates to friendship formation linked to economic mobility, in this section I examine why exposure to upper-income students might matter for lower-income students' college enrollment and employment outcomes. I focus on identifying if the relationship between exposure to upper-income students and long-term outcomes is exclusively driven by changes in access to (observable) school resources. I also try to disentangle the impact of exposure to upper-income students from exposure to higher-achieving students.

I focus on high school exposure to upper-income classmates to allow me to link students' classroom exposure to their college enrollment, graduation, and wages. Students are grouped into cohorts based on the year they are enrolled in grade 9. For example, students enrolled in grade 9 in 2009–2010 are grouped into the 2010 cohort. I observe seven cohorts of students: 2010 to 2016.[45] The data are at the student-school level. Students are assigned to their grade 9 school. Some students are enrolled in multiple schools in grade 9. Students across grade 8 reading (baseline) test-score groups appear to perform better when in classrooms with more upper-income classmates during their high school years, as shown in Figure 14.[46]

The positive relationship between a student's proportion of upper-income classmates and long-term outcomes may be driven by differences in access to school resources correlated with the proportion of upper-income classmates. For example, a lower-income student may be more likely to enroll in college if they attend schools with more upper-income peers because those schools also happen to have more experienced teachers. I find that students exposed to more upper-income students also have fewer novice teachers (3 or less years of experience) in high school, as shown in Figure 15. Students with 10pp more upper-income classmates are in classrooms with 2.6pp fewer novice teachers, on average.[47] The relationship between advanced course taking and exposure to upper-income students seems more ambiguous, although generally positively correlated with exposure to upper-income students. In comparison, school spending per pupil seems to decrease with higher exposure to upper-income students, as shown in Figure 16 Panel (a): Students with 10pp more upper-income classmates are in schools with 647 dollars lower spending per pupil.[48]

high-SES peers–42% of a student's top 5 female and male friends share at least one extracurricular activity.

[45] The income measure is based on the number of years on free/reduced price lunch. I observe each cohort for 10 years. For example, students in the 2010 cohort who never had free/reduced lunch between 2004 and 2013 are identified as higher income.

[46] These binned scatter plots are based on lower-income students in cohorts 2011 to 2016 and present the raw observational relationship (with no controls) between classroom exposure to upper-income students in high school and college enrollment and wages. Students are placed into three groups based on their standardized grade 8 reading test score: students who scored in the top 80th, between 20th and 80th, and 20th percentile of the cohort test score distribution. Test scores are standardized within the full sample of students who had taken the grade 8 test in a given year—92% of the students in the sample have grade 8 reading test scores.

[47] Teacher experience seems to matter most in the first few years of experience (see Rice, 2013).

[48] Spending patterns slightly vary across school by proportion upper-income students. Schools with 10 pp more upper-income

Access to school resources may vary both between and within schools. I find that within a school lower-income students in classrooms with (10pp) more upper-income students tend to have (3pp) fewer novice teachers compared to other lower-income students in the same school. The within school correlation between teacher experience and the proportion upper-income classmates suggests that even in a school access to school resources may vary with the proportion of upper-income classmates. This is consistent with Kalogrides and Loeb (2013) finding that lower-income students, compared to upper-income students in the same school, tend to enroll in classrooms with less experienced teachers.

6.1 Identification Strategy

One way the peer effects literature has gone around the question of if the relationship between peer composition and individual student outcomes is capturing differences in access to school resources (or selection) is by using (small) changes in cohort composition between adjacent cohorts in the same school. These marginal changes in cohort composition are less likely to change students' access to school resources. The assumption is that adjacent cohorts of students who attend the same school would have a similar school environment and the only difference between them is that some happen to have a slightly different cohort composition (e.g., more upper-income students) due to random draws from the school population that are unrelated to changes in school characteristics. Using cross-cohort deviations in peer composition to capture peer effects dates back to Hoxby (2001) and since then has been used extensively in the peer effects literature.[49]

Building on Hoxby (2001), I use within school cohort deviations in the proportion of upper-income peers to capture the impact of having more upper-income peers on lower-income students' outcomes. Note that in this section (unlike in prior sections) I use variation in grade 9 school cohort composition regardless of whether those students end up in the same classroom.[50] My preferred specification is shown in Equation (1):

$$Y_{isc} = \beta_0 + \beta_1 PropHighIncome_{-isc} + X'_{isc}\beta_2 + \delta_c + \delta_s + c \times \delta_s + \epsilon_{isc} \tag{1}$$

where $PropHighIncome_{-isc}$ is the share of student i's peers (excluding herself) in cohort c that are upper income; β_1 captures the impact of an unexpected change (residual of the linear school trend) in the composition of peers on the long-term outcome; and X'_{isc} is a vector of student i's characteristics (gender, race/ethnicity and math and reading grade 8 test scores). δ_s captures a school fixed effect to account for baseline school differences in student outcomes, and $c \times \delta_s$ captures school-specific time trends (c is a linear

students spend slightly more of their budget on instruction (0.7pp) and extracurriculars (0.6pp).

[49]For examples see Feld and Zölitz (2017), Lavy and Schlosser (2011) and Angrist and Lang (2004).

[50]I use variation in school-cohort instead of classroom-cohort because I cannot track the same classrooms over time and students self select into classrooms.

cohort trend). I also include cohort fixed effects, δ_c, to capture any cohort-specific changes in the sample. Because the treatment is at the school-cohort level, I cluster the standard errors at the school level. I run the regression only for lower-income students since I am interested in how exposure to upper-income peers impacts lower-income students' long-term outcomes.[51]

The key identifying assumption is that cohort deviations from school trend in the proportion of upper-income students are essentially random—they are uncorrelated with unobserved cohort changes that may be driving lower-income students' outcomes. This assumption is violated if a school offers more AP courses and in response more upper-income students enroll in the school. To address the school time-varying selection concern I include school-time trends in Equation (1), similar to Hoxby (2001). The school time trends capture systematic linear changes in cohort composition that may be driven by school and student unobserved changes. The source of variation that remains when including school trends is "unexpected shocks" (temporary) deviations from the school time trend in the proportion of upper-income peers.

School trends may not capture the pattern of school time-varying changes well. As an additional robustness check, in Tables 6 and 7 Models (5) and (6), I present falsification tests based on placebo cohort proportion upper-income peers replacing the true cohort composition with the cohort composition in the younger $(t-1)$ or older cohort $(t+1)$.[52] I show that adjacent cohorts' peer income composition do not appear to impact a students' own outcomes suggesting I am not capturing spurious correlations between the proportion of upper-income peers and time-varying school factors.

We might be concerned that changes in the proportion of upper-income students are capturing other simultaneous changes in lower-income students' characteristics that are correlated with their college enrollment and wages (common shocks). For example, lower-income students in cohorts with larger deviations from school trend in the proportion of upper-income students may happen to have higher family income which is driving their higher college enrollment. To assess the possibility of common shocks, I check whether lower-income students' demographic characteristics are correlated with deviations from school trend in the proportion of upper-income students. The proportion upper-income students does not seem to correlate with lower-income students' baseline characteristics (gender, race and immigrant status) suggesting that the estimates are not driven by simultaneous changes in lower-income students' characteristics as shown in Table A8. Lower-income students' parental income reported on financial aid data also appears to be no different when exposed to more upper-income peers, suggesting that the estimates are not driven by cohort specific

[51] Because it is very computationally intensive to run the regression with school-specific time trends, I ultimately residualized both the dependent variable (Y_{isc}) and independent variables ($PropHighIncome_{sc}$) on the fixed effects and time trends (δ_c, δ_s and δ_{sc}) and then regressed the residuals on one another. It provides me with the same standard errors and coefficients as in Equation (1).

[52] The falsification test is used by Lavy and Schlosser (2011) to identify if the impact of female peers is driven by time-varying school changes.

changes in lower-income students' household income that correlate with better long-term outcomes.[53]

Exposure to upper-income peers is highly correlated with exposure to higher-performing students (correlation of 0.53 among lower-income students). As such, we may be capturing the impact of exposure to high-achieving students, regardless of family income. To disentangle the two, I run another regression that controls for peer achievement. In-line with Section 4.3, high-achieving students are defined as those who performed in the top 24 percentiles of their grade 8 reading test score. To capture whether the effect is driven by changes in peer test scores, I control for the proportion of higher-achieving students in a cohort, $PropHighAchieve_{-isc}$. If the impact is driven by upper-income students' test scores, the coefficient on upper-income would approach 0 when I control for the proportion of high-achieving peers. The regression I run is shown in Equation (2) below:

$$Y_{isc} = \beta_0 + \beta_1 PropHighIncome_{-isc} + \beta_2 PropHighAchieve_{-isc} + +X'_{isc}\beta_3 + \delta_c + \delta_s + c \times \delta_s + \epsilon_{isc} \quad (2)$$

where $PropHighAchieve_{-isc}$ captures the proportion of high-achieving students in school s cohort c based on their standardized grade 8 reading score.

6.2 Source of Variation in the Proportion of Upper-Income Students

Adjacent cohort's proportion of upper-income students may vary due to random fluctuations in the proportion of upper-income students between cohorts in a school. For example, there may be random fluctuations in the proportion of upper-income students between cohorts attending the same school because a town doctor (upper-income family) happens to have two children of age groups that match certain cohorts and not others.

I use a Monte Carlo Simulation to assess whether the observed within school deviations from school trend in the proportion of upper-income students look like the variation that would result from random draws of upper-income students from the school population. For each school, I randomly generate the income of the students in each cohort using a binomial distribution function with p equal to the average proportion of upper-income students in the school across all years. I then compute the within school standard deviation of the residuals from a regression of the proportion upper-income students on school specific time trends. I repeat this process 1,000 times to obtain the empirical 90 percent confidence interval for the standard deviations of the residuals for each school.[54] Figure 18 shows that the distribution of schools' average

[53] Note that the financial aid data is based on a select group of students and the proportion of lower-income students who applying for financial aid slightly increases when lower-income students are exposed to more upper-income peers–by 0.5 percentage points for every 10 pp increase in the proportion of upper-income students.

[54] This method is based on Lavy and Schlosser (2011) simulation of deviations from school mean proportion female students.

simulated standard deviation from school mean is very similar to the observed schools' standard deviation in the proportion of upper-income students from school trend.[55] I find that 88 percent of the schools had a standard deviation within the empirical 90 percent confidence interval of the school's distribution of simulated standard deviations, which is close to what we would expect from random draws of the school population.

Using Equation (1), a standard deviation in the residual from school trend proportion of upper-income students is 2 percentage points.[56] At the 1st percentile are cohorts with 5.5 percentage points fewer upper-income students, and at the 99th percentile are cohorts with 5.8 percentage points more upper-income students. Table 5 summarizes the residual variation in the composition of the cohort and Figure 17 presents the distribution of the residual variation in cohort composition.

The median lower-income student is in a school-cohort with 582 students, 9% of whom are upper-income. As such, a 2 percentage point change in proportion of upper-income students for the median student is an increase in the number of upper-income students in their cohort from 52 to 64—that is from 1.5 to 1.9 upper-income students in a (median) class of 17 students.[57]

These temporary (small) shocks to cohort composition are unlikely to change the resources students have access to (e.g., teacher quality, AP courses offered, and school budgets). They also likely would not change classroom norms, which is a potential mechanism through which exposure to upper-income peers may impact long-term outcomes. These small changes in the number of upper-income peers may impact lower-income students through direct interactions like the passage of institutional knowledge or changes of expectations on what colleges may be feasible. It could also be through changes in teacher behavior or expectations in response to small changes in classroom income composition.[58]

6.3 Main Results

I find evidence consistent with the notion that a lower-income student in a cohort with a higher proportion of upper-income peers is (marginally) more likely to enroll in college and earn higher wages. I find that

[55] The right tale of the observed distribution of standard deviations is longer than the simulated distribution. This is likely in part because the simulated distribution is based on the average from multiple simulations. I rerun the main estimates excluding schools with standard deviations above 0.3 and the estimates remain consistent as shown in Table A24.

[56] The residual standard deviation is similar to the median standard deviation expected from random draws from the school population as shown in Figure 18

[57] Note that a student's cohort composition may not be representative of her actual exposure to upper-income students. I find that a 10-percentage-point increase in the proportion of upper-income peers in one's cohort increases lower-income students' proportion of upper-income classmates by 5.6 percentage points as shown in Table A9. The diluted impact of peer cohort composition on lower-income students' classroom exposure to upper-income peers may be in part due to within-school sorting by income. I find that a 10-percentage-point increase in the proportion of upper-income students in a cohort increased the level of within-school income sorting between classrooms by 1.3 percentage points, as shown in Table 10.

[58] Using this research design I am not able to identify why having more upper-income peers may have spillovers on lower-income students, but I can provide suggestive evidence on potential mechanisms like peer achievement and changes in access to (observable) school resources.

lower-income students are more likely to enroll in 4-year public colleges when exposed to more upper-income peers, as shown in Table 6. The results are based on Equation (1). The coefficient on the change in the upper-income share is 0.038 in Model (3) for lower-income students' 4-year college enrollment, implying that lower-income students' likelihood of enrolling in 4-year public colleges rises by 0.38 percentage points for every 10-percentage-point change in the share of their class that is upper income. I do not find strong evidence of an impact on a student's likelihood of graduating from college and enrolling in a selective college. The impact on college enrollment appears to be driven by students who ranked in the bottom 20th percentile of their grade 8 reading tests, as shown in Table A11.[59]

I also find evidence of a positive impact on average wages and income percentile rank.[60] The average quarterly wage of lower-income students by 2022 (by age 22–25) increased by 78 dollars (1.7%) as shown in Table 7 Model (3), and their percentile rank (within cohort) increased by 0.33 percentiles for every 10-percentage-point change in the share of upper-income students.[61]

The positive impact of exposure to upper-income students on wages likely does not operate exclusively through improved college enrollment. Zimmerman (2014) finds that the marginal admission to a public university in Florida for a student on free/reduced lunch increases their 4-year college enrollment by 14 percentage points and quarterly wages by $886.[62] This suggests that an increase in 4-year college enrollment of 0.4 percentage points should increase quarterly wages by $25. The increase in quarterly wages I observe is more than double that at $78, suggesting that the impact on quarterly wages likely does not operate only through the impact on lower-income students' 4-year college enrollment.

Adjacent cohorts' peer income composition do not appear to impact lower-income students' own outcomes as shown in falsification tests in Tables 6 and 7 Models (5) and (6). The results based on using $t-1$ and $t+1$ placebo cohorts show no detectable effects on any of the outcomes (coefficients are small, inconsistent and insignificant).[63] For example, using cohort $t+1$ a 10 p.p. change in proportion upper-income peers is associated with -.015 (p =0.5) change in lower-income students' 4-year college enrollment and -9.4 dollars (p =0.8) change in wages in early adulthood is. The lack of detectable effect suggests that the estimates I

[59] The estimates are consistent, albeit more statistically significant for college enrollment and graduation outcomes, when I run the regression without school time trends as shown in Tables 7 and 6 Models (1)–(2).

[60] Income percentile rank is based on ranking the full sample of students in a given cohort based on their average quarterly wages in 2022. Students who do not have wage data are assumed to earn 0 in that year

[61] The percent increase in wages is based on dividing the 78 dollars by the average lower-income students' quarterly wage in the sample in early adulthood ($4642). The estimate is based on imputing students who are missing unemployment insurance data with 0. If instead I only run the regression on students with employment data (60% of students) the wage gain is $105 for a 10 p.p. increase in the proportion of upper-income students—a 1.3% increase from the control mean for students with employment data of $7809. Exposure to upper-income students does not have a detectable impact on students' likelihood of being in the unemployment insurance data.

[62] This number is adjusted for inflation, assuming the $700 wage gain reported in Zimmerman (2014) is based on 2014.

[63] The only coefficient that remains similar in value though not significant is the coefficient on 4-year college enrollment when using cohort $t-1$, but it is not consistent with the other outcome coefficients.

find are not driven by spurious correlation between the proportion upper-income students and time-varying school factors and that there are no spillovers across cohorts.

Having an upper-income student might matter for a lower-income student independent of if the upper-income student is academically high- or low-achieving. To disentangle the impact of peer test scores on income, I control for the proportion of high-achieving students in a given cohort, as shown in Equation (2). If peer income impacts college enrollment only through peer test scores, the coefficient on the proportion of upper-income students should approach zero when I control for peer test scores.

I find that the impact of exposure to upper-income peers on college enrollment remains positive and consistent with previous estimates when controlling for peer test score as shown in Tables 7 and 6, Model (4)—if anything, it appears to be slightly larger. The consistent, slightly larger, estimates on the proportion of upper-income students suggest that there is something about being exposed to upper-income peers that impacts student college enrollment and wages through mechanisms other than peer achievement (orthogonal to peer test scores).[64]

One might wonder if the impact of exposure to upper-income students is driven by exposure to high-achieving upper-income students or lower-achieving upper-income students. In Table 9 I split peers into four categories: upper-income and high-achieving, upper-income and lower-achieving, lower-income and high-achieving and lower-income and lower-achieving. The pattern of results suggests that the group driving the positive effect on lower-income students' college enrollment is upper-income lower-achieving students.[65]

The relationship between the proportion of upper-income peers and long-term outcomes may operate through its short-term impact on students' test scores and high school behavioral outcomes (discipline and attendance). In Table 8 Model (3), I find that a 10-percentage-point increase in the proportion of upper-income peers decreases the probability of lower-income students receiving an out-of-school suspension by 0.43 percentage points and the proportion of days absent by 0.15 percentage points. A 10-percentage-point increase in the proportion of upper-income peers also appears to increase lower-income students' average reading test score by 0.02 standard deviations.[66]

[64] The patterns are consistent independent of how higher-achieving students are defined: using math (instead of reading) grade 8 test scores, average math and reading, grade 3 and/or average grades 3 to 8 test-scores as well as a continuous measure of peer achievement in Table A15.

[65] This is consistent with the notion that peer achievement might have a negative impact on lower-income students. In Tables A13 and A14 I present a horse-race between the impact of the proportion upper-income and the proportion high-achieving students in a cohort. The impact of exposure to high-achieving students appears to be negative. Feld and Zölitz (2017) similarly find using random assignment to sections at university that peer academic achievement may negatively impact lower-achieving students. On average, lower-income students score 0.2 standard deviations below the mean on their grade 8 reading test as shown in Table 4.

[66] The impact on test scores may be driven by a change in the composition of students taking the test. I do not find evidence that the change in peer income composition impacted the proportion of students missing reading test scores in high school. Most students took the Reading TAKS test in grade 9 (2010-2011) or the English I test in grade 9 (2012-2019).

The impact of exposure to upper-income students may be stronger between groups who share other common characteristics. I find some evidence suggesting that exposure to upper-income students may be stronger within racial/ethnic groups, but ultimately most estimates are noisy, as shown in Tables A17 to A19. The impact on 4-year public college enrollment is stronger for Black students in cohorts with more upper-income Black students (a 10pp change increases 4-year college enrollment by 4.3pp). The impact on wages also appears to be considerably stronger for White students exposed to more upper-income White students (a 10pp change increases wages and income rank in 2022 by 197 dollars and 1.3 percentile ranks).

One might ask if the impact of exposure to upper-income peers is capturing the impact of exposure to more white students. An increase in the proportion of upper-income students coincides with an increase in the proportion of white students, as shown in Table A12. I find that the impact of exposure to upper-income students is consistent with prior estimates controlling for changes in cohort racial/ethnic composition, as shown in Table A16, suggesting that the impact of exposure to upper-income peers is independent of changes in peer racial/ethnic composition.

6.4 Addressing Economic Segregation and the Role of Access to School Resources

An increase in the proportion of upper-income peers may impact students' college enrollment by changing students' course-taking patterns and/or access to experienced teachers. If the positive impact of exposure to upper-income peers is exclusively through access to school resources, then resource equalization policies may be enough to address concerns with economic segregation.

Table 10 presents the impact of having more upper-income peers on lower-income students' access to (observable) school resources: advanced course enrollment, teacher experience and spending per pupil. I find no (detectable) evidence that changes in peer income composition impact students' average teacher experience, number of advanced courses taken or spending per pupil–the coefficients are small and insignificant. For example, a 10 pp increase in the proportion of upper-income peers increases the proportion of novice teachers by 0.001 ($p = 0.592$) and number of AP courses a student takes by 0.02 ($p = 0.269$).[67] However, having upper-income peers may impact lower-income students' access to school resources in a way that we cannot observe in the data. For example, upper-income parents can volunteer to help plan school events or teach elective courses. Since policies can only impact access to school resources observed in the data, unobserved

[67] Another way to capture indirect effects of having more upper-income students in the district is to use cross-cohort variation in the proportion of upper-income students in district schools excluding the student's own school. I do not find any evidence of a district spillover effect on college enrollment and wages or access to school resources, as shown in Tables A21 and A22. In other words, changes in the proportion of upper-income students in schools other than a students' own have no impact on a students' own outcomes.

changes in access to school resources would likely require changes in cross-income exposure.

The positive (marginal) impact of exposure to upper-income peers on lower-income students suggests that at least some of the gains to improving cross-income exposure do not operate exclusively through changes in access to school resources. As such, resource equalization policies may not be enough to address the harms of economic segregation. To address the gap in exposure to upper-income peers documented in Section 4 we would want to swap upper- and lower-income students to improve lower-income students' exposure to upper-income peers. Since there are three income groups (upper-, middle- and lower-income) I control for the proportion of middle-income students to capture the impact of swapping a lower-income student with an upper-income student (and the other way around).

In Tables 11 and A20 I present the impact of changing the proportion lower- and upper-income students, controlling for the proportion of middle-income students in the cohort. By controlling for the proportion of middle-income students I try to simulate an experiment where upper- and lower-income students move around but middle-income students stay since their average exposure to upper-income peers is close to the integration benchmark. The results suggest that a 10 p.p. increase in the proportion upper-income students (holding constant the proportion of middle-income students, i.e. swapping lower-income students with upper-income students) would increase lower-income students' wages in early adulthood by 2.1% (p =0.02). Alternatively, a 10 p.p. increase in the proportion lower-income students (holding constant the proportion of middle-income students) has no detectable impact on upper-income students wages (-0.6% (p =0.5)). Under the swap 10% counterfactual, the slope of the relation implies a 5% decrease in the gap between upper- and lower-income students in quarterly wages in early adulthood.

The positive impact on lower-income students of increased exposure to upper-income peers and the lack of detectable impact on upper-income students of increased exposure to lower-income peers suggests that improving cross-income exposure could be a win-win/neutral situation. Note that the estimates are based on temporary shocks in exposure to upper-income peers within the same school. As such, it captures the impact on lower- and upper-income students who remain in the same school, but not the impact on upper- and lower-income students who would have to move schools to improve cross-income exposure. It also capture the impact of temporary changes which may be a lower-bound on potential gains from long-term changes in the proportion of upper-income peers on lower-income students if long-term changes are more likely to improve access to school resources. Importantly, these estimates assume that the slope of the relationship between the proportion of upper-income peers and long-term outcomes is linear.

To bound the potential wage gains from exposure to upper-income students, I run regressions using variation across schools in the proportion of upper-income students. In Table A23 Model (1) I control for student test scores and demographic characteristics, but only include cohort fixed effects. In Model (2) I include middle school-cohort fixed effects and in Model (3) I include district fixed effects. In Mode (2) I use variation in the proportion of upper-income students in high school between students who attended the same middle-school cohort, and in Model (3) I use variation among students in the same district who happen to be in different cohorts or high schools that had a different proportion of upper-income students. These models are subject to more selection concerns than my main specification. For example, there is likely a reason why two students in the same cohort attended the same middle school, but one decided to attend a different high school. Nevertheless, it can give a sense of the potential gain from larger variations in the proportion of upper-income students.[68] The average wage gain in Table A23 ranges from \$86 to \$110 for a 10 percentage-point increase in the proportion of upper-income students in a students' grade 9 school cohort. The similar estimated wage gain compared to the main specification (using small variation within a school in the proportion of upper-income students) suggests that the estimate from the main specification likely only slightly underestimate the potential gain from increasing exposure to upper-income students.

6.5 Robustness Checks: Treatment Definition and Measurement Error

The deviations in the proportion of upper-income students may be capturing small measurement errors in a students' income, i.e., lower-income students' peer income composition did not change it just happens to be that one student who should have been assigned one year on free/reduced lunch was not assigned to free/reduced lunch due to administrative or other errors. To assess if the proportion of upper-income students (students never on free/reduced lunch status) is capturing changes in students' peer income I regress lower-income students' average cohort income (excluding self) using a continuous measure of income (e.g. reported parental income in FAD application) on the proportion of (upper-income) students never on free/reduced lunch status. I find that a 10pp increase in the proportion of upper-income students–defined as students never on free/reduced lunch–is associated with a 5 thousand dollars higher average cohort income based on financial aid applications and 8 pp fewer cohort average proportion of years on free/reduced price lunch status as shown in Table A25.

The treatment–deviations from high school trends in the proportion of upper-income students–might be capturing changes in cohort proportion upper-income peers that date back to earlier school years. In other words, lower-income students in cohorts with more upper-income students in high-school likely also had more upper-income students in middle and elementary schools. I find that a 10pp increase in the proportion of

[68] A standard deviation in the residual variation in the proportion of upper-income students ranges between 15 and 9 percentage points more upper-income students in Table A23, Models (1)-(3).

upper-income students in high-school is associated with a 6pp higher proportion of upper-income students in grade 8. The correlation between the proportion upper-income in middle and high school suggests that the treatment may be capturing the cumulative impact of deviations from school trends in the proportion of upper-income students on lower-income students. That said, my main specification controls for students' own grade 8 reading and math test-score and so in so far as students' grade 8 test-scores are capturing the impact of prior exposure to upper-income students, the remaining impact of exposure to upper-income students is capturing the impact of high-school exposure.

To capture the impact of exposure to upper-income students in high school independent of middle school exposure and to address the concern that grade 8 peer test-score may be a function of grade 8 exposure to upper-income peers, I include fixed effects for students' grade 8 school-cohort as shown in Table A26 Model (5). By including grade 8 school-cohort fixed effects I am limiting the variation to students who attended the same grade 8 school and cohort but happen to attend high schools with differing deviations from school trend in the proportion of upper-income students. The coefficients on the proportion of upper-income peers are generally consistent but insignificant when controlling for grade 8 school-cohort, with the exception of public 4-year college enrollment which remains consistent and significant.

I also present estimates on the impact of peer achievement using earlier student test-scores that may not have been impacted by changes in cohort peer income composition. Ideally, I would want to control for student achievement measured before students enroll in school, but in the absence of this I use grade 3 test-scores which are the earliest test-scores I have for students. Table A15 Model (4) shows that the coefficients on the impact of the proportion of upper-income peers is consistent independent of if I control for grade 3 or grade 8 student peer reading test-scores.

6.6 The Role of Friendship Formation

Assume that a student's exposure to upper-income peers has a causal impact on her income in adulthood (as suggested in the results of this paper). If the mechanism requires friendship formation, then the impact of exposure to upper-income students on wages would be smaller than the impact of befriending higher-income students on wages. If instead the impact of exposure to upper-income peers does not require friendship formation and is due to other factors related to exposure, then the impact of exposure to upper-income students may be larger than the impact of befriending higher-income students. Ideally, I would want to compare the causal relationship between friendship and wages to that between exposure and wages. To do so, I would need random variation in each of exposure and friendship. In the absence of this, I examine how the raw (no controls) relationship between friendship and wages compares to the relationship between exposure and wages in the Add Health data. In the Add Health data, I have information on students' reported income by age 24–32.

I find that the correlation between low-SES students' upper-income peers and own income is slightly stronger than the correlation between students' proportion of high-SES friends and own income in early adulthood: correlation 0.07 relative to 0.03. The stronger correlation between exposure and students' income suggests that the relationship between peer composition and long-term outcomes may not require lower-income students to be close friends with upper-income students. Since the Add Health friendship data is based on listing students' top five friends, I cannot eliminate the possibility that the relationship between peer composition and long-term outcomes may require (weak) friendships with upper-income peers. That said, it suggests that information on a lower-income student's exposure to upper-income peers may be more predictive of her wage in adulthood than information on her proportion of close upper-income friends.

I can similarly compare the Chetty et al. (2022) measure of the relationship between economic connectedness and income in adulthood to the relationship between exposure to upper-income students and long-term outcomes captured in this paper. Using a movers design, Chetty et al. (2022) find that moving to a neighborhood with 1 unit higher economic connectedness increases income in adulthood by 30.7%. The slope of the relationship suggests that a 10 percentage-point difference in a schools' proportion upper-income peers (equivalent to a 0.16 units difference in economic connectedness) would increase income in adulthood by 4.9%, which is much larger than the impact on wages in early adulthood found in this paper (1.7% increase in wages).[69]

To compare the estimates of the impact of economic connectedness in Chetty et al. (2022) to the estimates of the impact of exposure to upper-income peers in this paper, we need to assume that for a lower-income student, the effect of a 10-percentage-point change in the proportion of upper-income peers in the same school is equivalent to moving to a school with a 10-percentage-point difference in the proportion of upper-income peers. I will call this assumption the "movers assumption". The movers assumption is violated if schools with consistently more upper-income peers benefit from having upper-income students move more resources to the school over the long run (such as more AP courses), while an equivalent temporary shock to peer income composition in a school would not allow for enough time for peer income to change students' access to resources.

Here, the weaker relationship between exposure to upper-income peers and long-term outcomes relative to measures of economic connectedness may be driven by a number of factors. Those include that the

[69] The conversion from economic connectedness units to school proportion of upper-income students is based on the slope of the relationship between a schools' economic connectedness as captured by Chetty et al. (2022) and average lower-income students' proportion of upper-income classmates as captured in Section 5 in this paper.

effect of a shock to a school's cohort composition is not equivalent to moving to a school with more upper-income peers (i.e., the movers assumption does not hold). If the movers assumption holds, then the smaller effect of exposure to upper-income peers found in this paper could be because economic connectedness is capturing something that is particularly important for long-term outcomes that is not captured by exposure to upper-income students.[70]

7 Discussion and Conclusion

I find that that lower-income students are generally exposed to very few upper-income students through grades 5 to 12 in Texas and that students are more clustered by income than they are by achievement. Lower-income students' exposure to upper-income peers is driven mainly by district and school segregation by income. How students are sorted within school classrooms has a much smaller impact on the average lower-income student's exposure to upper-income peers. Nevertheless, classrooms may be an easier policy lever, and some lower-income students would have gained considerably had students instead been randomly assigned to classrooms, particularly in high school.

Using the residual from school trend cross-cohort variation within schools, I find that having more upper-income peers improves lower-income students' college enrollment and quarterly wages in early adulthood. The effect of peer income does not appear to be driven by differences in peer test scores, suggesting that we should think of peer income spillovers as operating separately (and potentially despite) peer achievement spillovers. Changes in cross-cohort composition do not appear to change students' access to school resources like the proportion of novice teacher or number of AP courses, suggesting that the impact of exposure to upper-income peers captured in this paper is not driven by changes in access to school resources. This implies that policies that aim to equalize access to school resources would not fully address the missed-out-on potential gain from cross-income exposure.

The high level of income segregation documented in this paper and the positive impact of upper-income peers on lower-income students' long-term outcomes suggest that income desegregation policies may be particularly beneficial for economic mobility. Decreasing segregation by income also appears to be a win–win/neutral situation, as I find that upper-income students are not (negatively) impacted by exposure to lower-income peers. If anything, prior work by Rao (2019) finds using a school desegregation policy in India that having lower-income classmates makes upper-income students more prosocial (more likely to volunteer

[70]There are a number of other potential reasons for why the estimates are different which include that in Chetty et al. (2022) the estimate is based on changes in neighborhood and not school economic connectedness. If neighborhood composition has a different effect from school composition, then this could also explain the difference in estimates. It could also be because, in this paper, I capture income in early adulthood, which may be less stable and understates the gain to exposure.

for charitable causes and more giving) and less likely to discriminate against lower-income students.

The estimates of the impact of exposure to upper-income peers are based on small (and temporary) variation in peer income composition. The advantage of using small (temporary) shocks in peer income composition is that these shocks are less likely to impact lower-income students' access to school resources, and so it helps us isolate the effect of peer income spillovers. Nevertheless, the use of temporary shocks also means that the estimates of the impact of peer income might not generalize to policies that result in permanent changes in peer income composition. If we think that permanent changes in the proportion of upper-income peers would also allow for more time for changes in access to school resources like experienced teachers, then the estimates from this paper would underestimate the potential gain from desegregation.

The impact of exposure to upper-income students may be context dependent. Future research should examine how and when peer income matters. For example, it is possible that having upper-income peers matters less when access to information on colleges and employment is more available (e.g., Dynarski, Libassi, Michelmore and Owen, 2021) and/or in industries less dependent on job referrals. It also might matter less if the likelihood of enrolling in certain colleges and working in certain industries is equalized across income groups (that is, if college enrollment and employment norms do not differ across groups). Future work would benefit from surveys that shed light on the differential availability of information to upper- and lower-income students and the role of classroom composition as it relates to norm setting.

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9 Main Tables and Figures

Table 1: Texas State Public School Student Demographics: Cohorts 2012-2014

Variable	Mean
Asian-American	.048
	(.213)
Black Students	.141
	(.348)
White Students	.320
	(.466)
Hispanic Students	.516
	(.500)
Enrolled in Title 1 School	.572
	(.495)
Free/Reduced Lunch Status	.608
	(.488)
Special Education	.094
	(.292)
Gifted Program	.106
	(.307)
Enrolled in Bilingual Program	.027
	(.161)
English Language Learner	.262
	(.440)
Any Vocational Ed	.353
	(.478)
Number of Students	1128554

*Notes.*This table summarizes demographic characteristics of the three cohorts of students I follow from grade 5 to expected grade 12. The demographic characteristics are based on student demographics (including free/reduced lunch status in fifth grade). The average is weighted by number of students across three cohorts. A cohort is defined by the year I observe them enrolled in grade 5 (2012, 2013 or 2014). The number in the brackets is the standard deviation.

Table 2: The Role of Academic Preparation in Accounting for Within-School Differences in Exposure to Upper-Income Students

	(1)	(2)	(3)	(4)
Upper-Income	0.115	0.0997	0.0935	0.0927
	(0.0018)	(0.0016)	(0.0013)	(0.0013)
School Fixed-Effect	X	X	X	X
Cohort-Year Fixed-Effect	X	X	X	X
Grade 8 Test-Scores		X	X	X
Algebra I by G8		X	X	X
Attendance and Suspension G8				X
N	4207473	4207473	4207473	4207473
R2	0.916	0.926	0.931	0.931

The upper-income variable is an indicator variable that takes value 1 if a student is upper income. Model 1 includes school and cohortxyear fixed effects. Model 2 additionally includes test-score controls: grade 8 reading and math test scores as well as indicators for missing a test-score. Model 3 additionally includes an indicator for whether a student has taken Alegbra I by grade 8. The sample is limited to students in cohorts 2012 to 2014 (based on grade 5 entry) high-school enrollment years. Standard errors are clustered at the school level. The attendance and suspension variables are the following: number of days absent, number of member days, total suspensions (in- and out-of-school) and a missing attendance indicator. Attendance and suspension data are based on expected grade 8 school years.

Table 3: Number and Size of 9th Grade and Demographics of 9th Graders in Texas

Cohort	N. Schools	Median Size	High-Income	High-Achieve	Black	Hispanic	White
2010	1981	68	.276	.295	.14	.472	.314
2011	2067	65	.275	.277	.138	.481	.31
2012	2245	65	.26	.274	.137	.473	.293
2013	2254	68	.255	.247	.137	.481	.286
2014	2266	68.5	.255	.23	.136	.483	.288
2015	2297	71	.253	.237	.135	.491	.284
2016	2275	73	.243	.241	.136	.499	.275

*Notes.*This table summarizes characteristics of the 2010 to 2016 9th grade cohorts. The median school size is based on equally weighting each school. The demographics are student averages weighted by the number of students enrolled.

Table 4: Grade 8 Standardized Reading Scores for 9th Graders

Cohort	% Missing	All	High-Income	Low-Income	High-Achieve
2010	7.4	.017	.384	-.246	.686
2011	8	.024	.409	-.246	.723
2012	6.8	-.011	.409	-.287	.734
2013	7.1	.082	.576	-.201	1.003
2014	8.5	-.026	.172	-.159	.907
2015	7.4	-.088	.098	-.214	.943
2016	7.6	-.198	.139	-.403	1.044

*Notes.*This table summarizes test scores of the 2010 to 2016 9th grade cohorts. The test scores are based on the grade 8 reading test and are standardized within the full population of students who took the test in a given year. “High-Achieve” students are those who scored in the top 24 percentiles of their cohort distribution of standardized test scores.

Table 5: Variation of interest: Between Cohorts 2010 and 2016–Residual Change in Income and Achievement of 9th Graders

Statistic	high-income	high-achieve	high-incomexblack	high-incomexhisp	high-incomexwhite
Standard Deviation	.02	.033	.007	.01	.029
1st Percentile	-.055	-.094	-.018	-.027	-.079
5th Percentile	-.027	-.047	-.01	-.014	-.043
10th Percentile	-.018	-.031	-.006	-.009	-.028
90th Percentile	.018	.032	.007	.009	.027
95th Percentile	.028	.048	.01	.015	.045
99th Percentile	.058	.094	.018	.031	.092

*Notes.*This table summarizes the residual variation in the proportion of high-income students, the proportion of high-achieving students, the proportion of high-income and Black students, the proportion of high-income and Hispanic students and the proportion of high-income and White students. The residual variation is based on Equation (1): it is the residual variation after including cohort and school-trend controls. It is based on the sample of low-income students, i.e., it is weighted by the number of low-income students enrolled, which is the population of interest here.

Table 6: Impact of Proportion Upper-Income Students on College Enrollment for Lower-Income Students

	Main effects				Falsification test	
					t+1	t-1
	(1)	(2)	(3)	(4)	(5)	(6)
Enrolled in College/University						
Proportion Upper-Income	0.0795	0.108	0.0455	0.0640	-0.00731	0.000225
	(0.0240)	(0.0246)	(0.0246)	(0.0249)	(0.0282)	(0.0271)
Group Mean	0.380					
Enrolled in a Public 2yr College						
Proportion Upper-Income	0.0854	0.105	0.0374	0.0517	-0.0108	-0.0261
	(0.0251)	(0.0263)	(0.0244)	(0.0253)	(0.0274)	(0.0256)
Group Mean	0.290					
Enrolled in a Public 4yr College						
Proportion Upper-Income	0.0411	0.0542	0.0379	0.0479	-0.0151	0.0325
	(0.0165)	(0.0163)	(0.0193)	(0.0194)	(0.0213)	(0.0217)
Group Mean	0.140					
Enrolled in a Selective University						
Proportion Upper-Income	0.00557	0.00892	0.00305	0.00568	0.00249	-0.00401
	(0.00465)	(0.00474)	(0.00580)	(0.00590)	(0.00637)	(0.00712)
Group Mean	0.0200					
School time trend			X	X	X	X
Proportion High-Achieving Peers		X		X		
N	1013905	1013905	1013905	1013905	844665	868245
N Clusters	2141	2141	2141	2141	2034	2076

Standard errors are in parentheses and clustered at the school level. Coefficients are based on Equation (1). Models (1) and (2) do not include school time trends. College enrollment outcomes include cohorts 2010–2016. Models (2) and (4) include both the proportion of upper-income and higher-achieving peers in the cohort. Group Mean is the average for lower-income students in the sample. Models (5) and (6) are placebo tests using the proportion of upper-income students of cohort $t+1$ Model (5) or $t-1$ Model (6).

Table 7: Impact of Proportion Upper-Income Students on College Graduation and Wages for Lower-Income Students

	Main effects				Falsification test	
					t+1	t-1
	(1)	(2)	(3)	(4)	(5)	(6)
Graduated College/University						
Proportion Upper-Income	0.0552	0.0589	0.0272	0.0308	-0.00720	-0.00125
	(0.0206)	(0.0206)	(0.0226)	(0.0227)	(0.0245)	(0.0287)
Group Mean	0.160					
Average Quarterly Wage 2022						
Proportion Upper-Income	614.8	678.8	778.5	894.1	-93.46	-430.6
	(323.7)	(326.5)	(398.4)	(401.5)	(436.6)	(454.4)
Group Mean	4642.8					
Income Percentile 2022						
Proportion Upper-Income	1.399	2.184	3.300	3.745	0.337	-1.448
	(1.380)	(1.401)	(1.648)	(1.664)	(1.763)	(2.017)
Group Mean	46.80					
School time trend			X	X	X	X
Proportion High-Achieving Peers		X		X		
N	700245	700245	700245	700245	695382	560867
N Clusters	1992	1992	1992	1992	1967	1929

Standard errors are in parentheses and clustered at the school level. Coefficients are based on Equation (1). Models (1) and (2) do not include school time trends. Models (2) and (4) include both the proportion of upper-income and higher-achieving peers in the cohort. Group Mean is the average for lower-income students in the sample. College enrollment outcomes include cohorts 2010–2016. College graduation and wages include cohorts 2010–2014. Models (5) and (6) are placebo tests using the proportion of upper-income students of cohort $t+1$ Model (5) or $t-1$ Model (6).

Table 8: Impact of Proportion Upper-Income Students on High School Academic and Behavioral Outcomes

	Model 1	Model 2	Model 3	Model 4
Reading/English I Test Score				
Proportion Upper-Income	0.340	0.476	0.185	0.293
	(0.0758)	(0.0788)	(0.0592)	(0.0621)
Group Mean	-0.300			
N	948421			
Missing Reading/English I Test Score				
Proportion Upper-Income	0.00527	0.0210	0.0123	0.0154
	(0.0179)	(0.0187)	(0.0255)	(0.0258)
Group Mean	0.0600			
N	1013905			
Proportion of Days Absent				
Proportion Upper-Income	-0.0200	-0.0158	-0.0152	-0.0136
	(0.00703)	(0.00695)	(0.00556)	(0.00557)
Group Mean	0.0900			
N	979552			
Any Out-of-School Suspension				
Proportion Upper-Income	-0.00383	-0.00728	-0.0426	-0.0437
	(0.0260)	(0.0265)	(0.0199)	(0.0200)
Group Mean	0.210			
N	1013905			
Any In-School Suspension				
Proportion Upper-Income	-0.0436	-0.0457	-0.0533	-0.0499
	(0.0424)	(0.0425)	(0.0280)	(0.0281)
Group Mean	0.360			
N	1013905			
School time trend			X	X
Proportion High-Achieving Peers		X		X

Standard errors are in parentheses and clustered at the school level. Coefficients are based on Equation (1). Group Mean is the average for lower-income students in the sample. All outcome regressions are based on the 2010–2016 cohorts. The test score outcome has fewer observations since 6% of students are missing their reading scores. Most students take the Reading/English I test in grade 9. For students who took the test in 2010 and 2011, their scores were based on the Reading TAKS test. For students who took the test after 2011, their scores were based on the English I STAAR test. All raw scores were standardized based on the distribution of students who took the test that year.

Table 9: Impact of Changes in Income and Achievement Composition on Lower-Income Students: 4 Groupings

	(1) Any College	(2) 2yr Public	(3) 4yr Public	(4) Selective	(5) Grad Any	(6) Wage 2022	(7) Income Percentile
Proportion Upper-Income and High-Achieve	-0.0331	-0.000816	0.00821	-0.00956	0.0315	557.9	1.778
	(0.0337)	(0.0312)	(0.0254)	(0.00862)	(0.0309)	(520.6)	(2.129)
Proportion Upper-Income and Lower-Achieve	0.130	0.0813	0.100	0.0125	0.0288	639.9	2.229
	(0.0294)	(0.0299)	(0.0218)	(0.00687)	(0.0270)	(452.9)	(1.958)
Proportion Low-Income and High-Achieve	0.0127	-0.0393	0.0539	-0.00997	-0.0545	-1361.4	-6.289
	(0.0462)	(0.0403)	(0.0428)	(0.0102)	(0.0427)	(503.9)	(2.186)
Proportion Low-Income and Lower-Achieve	0.0463	0.0335	0.0553	0.00323	0.0169	-207.7	-2.163
	(0.0193)	(0.0203)	(0.0141)	(0.00408)	(0.0179)	(251.2)	(1.130)
N Clusters	2141	2141	2141	2141	1992	1992	1992
N	1013905	1013905	1013905	1013905	700245	700245	700245

Standard errors are in parentheses and clustered at the school level. The coefficients are based on Equation (1) but instead of the main independent variable (proportion upper-income students), students are split into four groups based on if they are upper-income and/or higher-achieving (test score in the top 24 percentiles of grade 8 reading test). Models (1)–(4) include cohorts 2010–2016 and Models (5)–(7) include cohorts 2010–2014.

Table 10: Impact of an Increase in the Proportion of Upper-Income Students on Access to School Resources

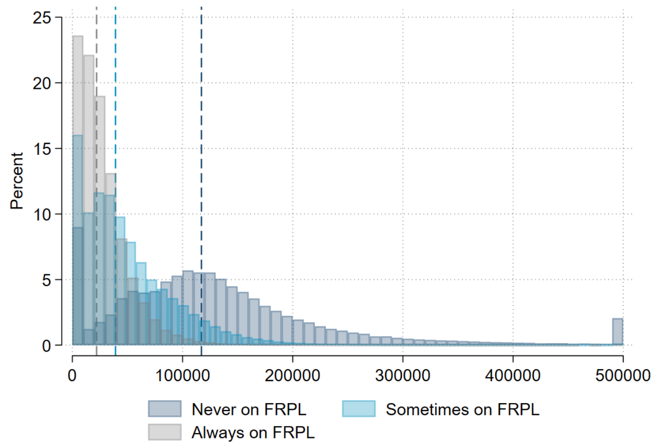
	(1) Class Sorting	(2) Teacher Experience	(3) Novice Teachers	(4) Spending	(5) Advanced Courses	(6) AP Courses
Proportion Upper-Income	0.129	0.296	0.0121	-585.7	0.143	0.232
	(0.0138)	(0.403)	(0.0226)	(483.0)	(0.307)	(0.210)
Group Mean	0.089	10.610	0.281	9835.850	2.558	1.423
N Clusters	1965	1982	1982	1749	2141	2141
N	841215	736994	736994	707294	1013905	1013905

Standard errors are in parentheses and clustered at the school level. Coefficients are based on Equation (1). Model (1) includes cohorts 2011–2016 because the classroom data needed to calculate the within-school variance ratio are only available starting in 2011. Models (2)–(4) include cohorts 2012–2016 because teacher and school budget data linked to classrooms are only available starting in 2012. Spending is average school spending per pupil in a given year. Models (5)–(6) include cohorts 2010–2016.

Table 11: Impact of Proportion Lower-Income Students, Holding Constant Mid-Income Students: on Upper-Income Students

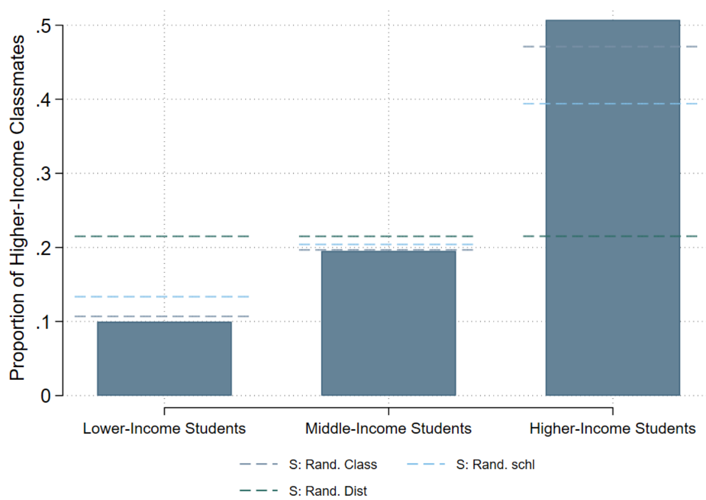
	(1) Any College	(2) 2yr Public	(3) 4yr Public	(4) Selective	(5) Grad Any	(6) Wage 2022	(7) Income Percentile
Proportion Lower-Income	-0.0354	0.00269	-0.0432	0.00184	-0.0727	-456.2	-1.261
	(0.0304)	(0.0325)	(0.0330)	(0.0207)	(0.0416)	(669.9)	(2.296)
Proportion Middle-Income	-0.0639	-0.0213	-0.0744	-0.00540	-0.0883	-650.8	-1.935
	(0.0251)	(0.0277)	(0.0274)	(0.0184)	(0.0338)	(557.2)	(1.909)
Group Mean	0.690	0.490	0.420	0.160	0.440	7414.4	54.7
N Clusters	1945	1945	1945	1945	1818	1818	1818
N	771243	771243	771243	771243	549280	549280	549280

Figure 1: Distribution of Parental Income by Free/Reduced Lunch Status



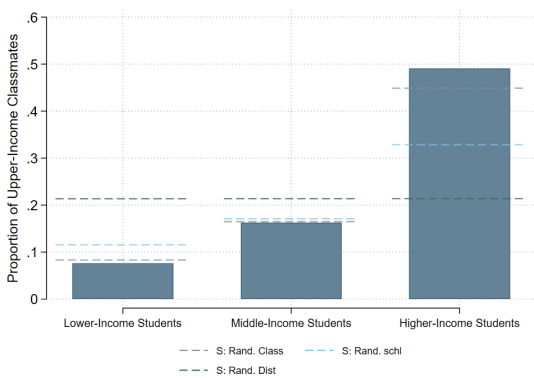
Notes: Parental Income is based on the adjusted parental gross contribution listed on financial aid applications from 2017 to 2022 linked to the cohort of students enrolled in grade 5 in 2012, 2013 and 2014. The vertical lines are the median income for each group. Outlier students with parents who have listed an income above 500,000 are top-coded so that we are better able to see the variation, but those observations are not top-coded when calculating the median and mean. Financial aid data are not available for 48%, 65% and 70% of students never, sometimes, and always on free/reduced lunch, respectively.

Figure 2: Exposure to Higher-Income Students: Observed Relative to Random Assignment

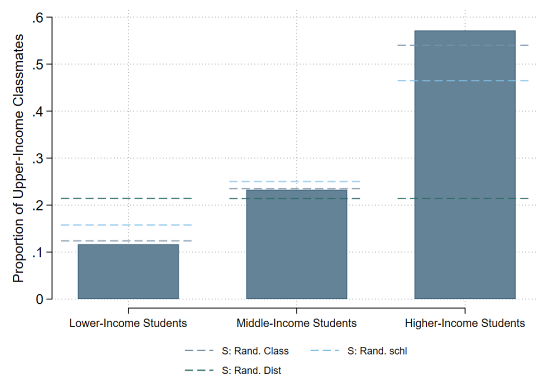


Notes: The bars capture the cumulative proportion of classmates that are higher-income calculated as the total number of higher-income students a given student is in a classroom with from grade 5 to expected grade 12 (excluding own status) divided by the total number of students in each classroom from grade 5 to expected grade 12 (excluding self). The average exposure is weighted by the number of students in each group. The dashed horizontal lines present the various benchmarks for integration. "'S: Rand. Dist" lines capture the expected proportion of higher-income classmates had students been randomly assigned to districts in each year-cohort: district integration benchmark. The "S: Rand. Schl" lines capture the expected proportion of higher-income classmates had students been randomly assigned to schools within a district in each year-cohort (holding constant district composition): school integration benchmark. The "S: Rand. Class" lines capture the expected proportion of higher-income classmates had students been randomly assigned to classrooms within a school in each year-cohort (holding constant school composition): classroom integration benchmark.

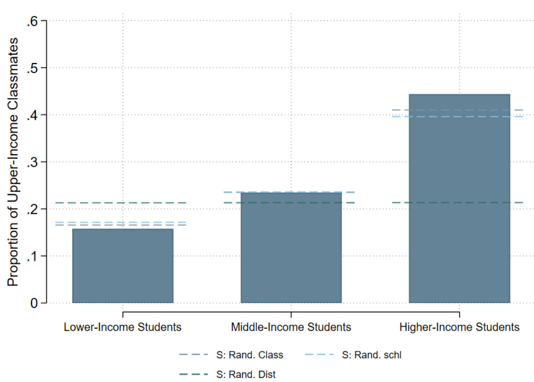
Figure 3: Exposure to Higher-Income Students: Observed Relative to Random Assignment



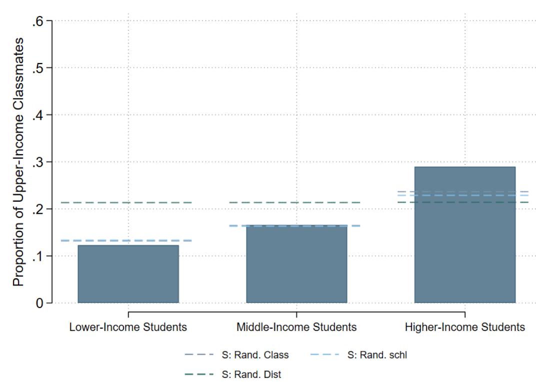
(a) City



(b) Suburb



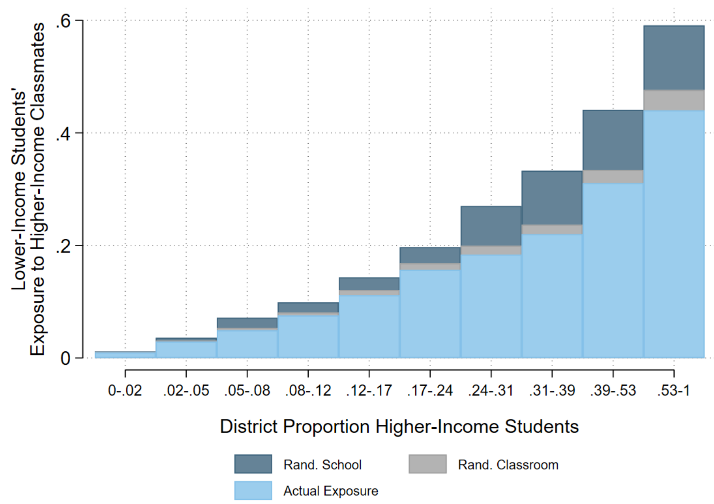
(c) Rural



(d) Town

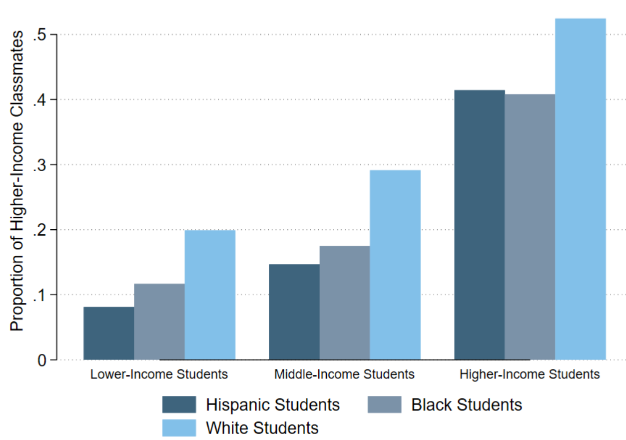
Notes: Similar to Figure 2 but split students by district type. Students are assigned district type based on the district they enroll in grade 5. District type is based on NCES categorization of districts.

Figure 4: The Percentage Point Gap in Exposure to Higher-Income Students Increases as the Proportion of Higher-Income students in the District Increases



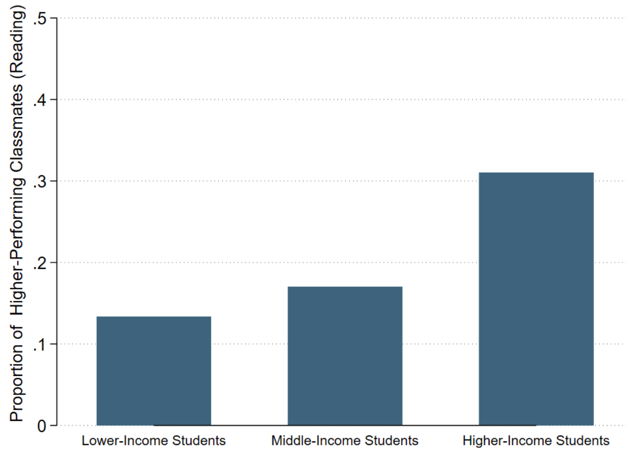
Notes: This plot presents lower-income students' exposure to higher-income students in districts with various proportions of higher-income students. Exposure is defined as the average proportion of higher-income classmates in a year. The light blue bar shows the observed proportion of higher-income students in lower-income students' classrooms. The navy bar presents the expected proportion of higher-income students had students been randomly assigned to schools in the district: school integration benchmark. The gray bar presents the expected proportion of higher-income students had students been randomly assigned to classrooms in the school: classroom integration benchmark. Districts are split into ten percentiles based on the distribution of the proportion of higher-income students in the district in a given school-year. The distribution is weighted by the number of students in each district (independent of income status). The lower and upper bound for each of the percentiles is shown on the x-axis.

Figure 5: Gap in Exposure to Higher-Income Students Exists Independent of Students' Race/Ethnicity



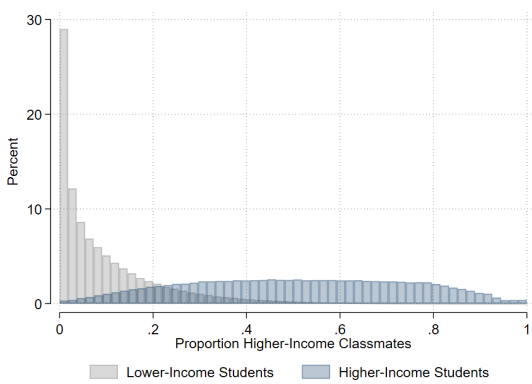
Notes: This plot captures the proportion of higher-income classmates across grades 5 to 12 for each income and racial/ethnic group. Higher-income students are defined as students never on free/reduced lunch.

Figure 6: The gap in Exposure to Higher-Performing (Top 24 Percentiles) Students is Smaller than the Gap in Exposure to Upper-Income Students

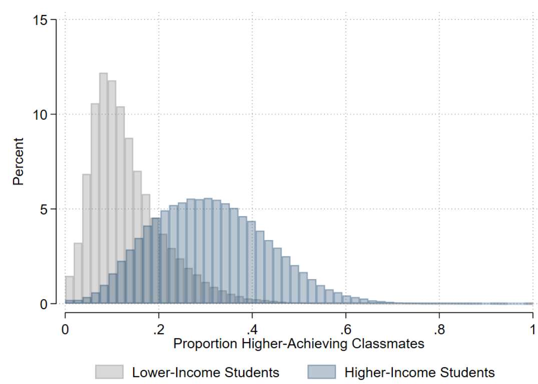


Notes: This plot captures students' cumulative proportion of higher-performing classmates between grade 5 to expected grade 12. I define higher-performing students as students who performed in the top 24 percentiles of test score based on the grade 4 standardized reading test. The percentiles are based on the distribution of students who have a grade 4 test score. Approximately 5% of students are missing grade 4 reading test scores.

Figure 7: At the 25th Percentile, Lower-Income Students Have 1% Upper-Income and 7% Higher-Achieving Classmates



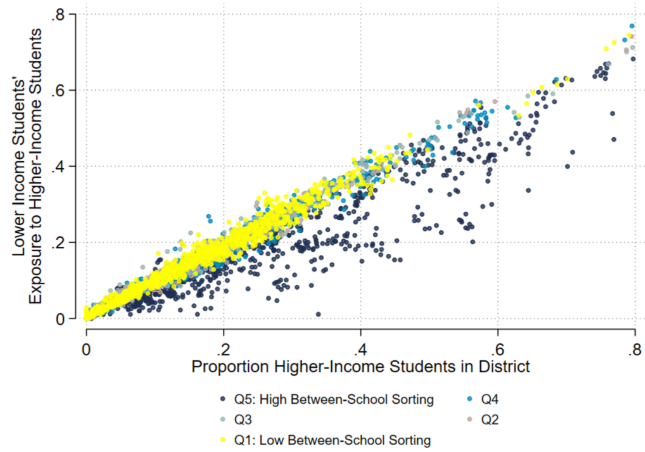
(a) Proportion of Upper-Income Classmates



(b) Proportion of Higher-Achieving Classmates

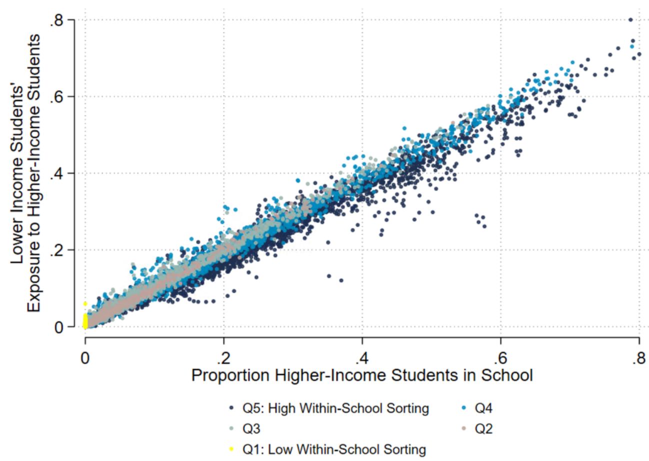
Notes: Every time a student is in a classroom with an upper-income/higher-achieving student, this is counted as one interaction. Histograms present the distribution of the proportion of classmates in cohorts 2012–2014 who are upper-income/higher-achieving between G5-12 for higher- and lower-income students. The average number of classroom interactions between grades five and twelve is approximately 2000.

Figure 8: Conditional on District Composition, Lower-Income Students' Exposure to Higher-Income Classmates



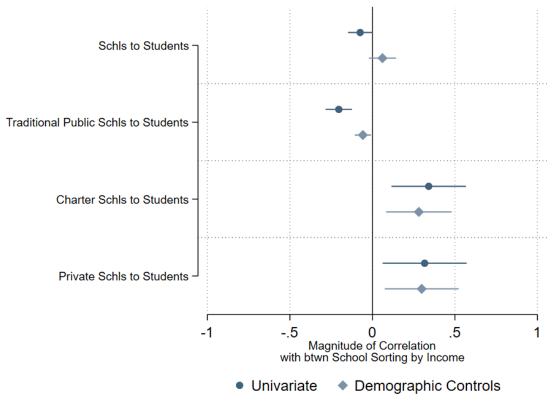
Notes: Each dot represents a district-grade. I only include districts with more than 50 lower-income students enrolled in a grade across three cohorts. The darker color represents district-grades with more sorting between schools, while the lighter dots represent district-grades with less sorting between schools. Sorting is captured by the variance ratio.

Figure 9: Conditional on School Composition, Lower-Income Students' Exposure to Higher-Income Classmates

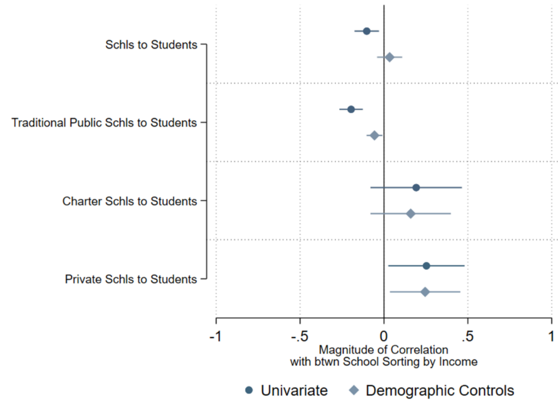


Notes: Each dot represents a school-grade. I only include schools with more than 50 lower-income students enrolled in a grade across three cohorts. The darker color represents school-grades with more sorting within school, while the lighter dots represent school-grades with less sorting within schools. Sorting is captured by the variance ratio.

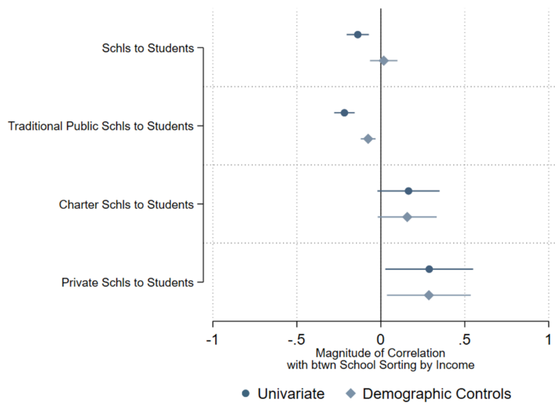
Figure 10: Between-School Sorting in Public Schools is Higher in Districts with More Charter and Private School Options



(a) Grades 3 to 5



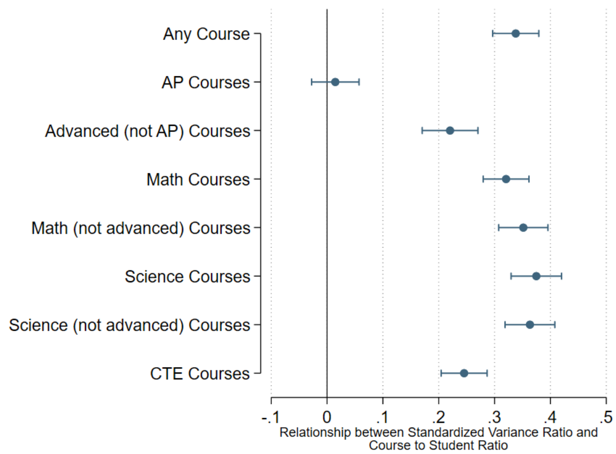
(b) Grades 6 to 8



(c) Grades 9 to 12

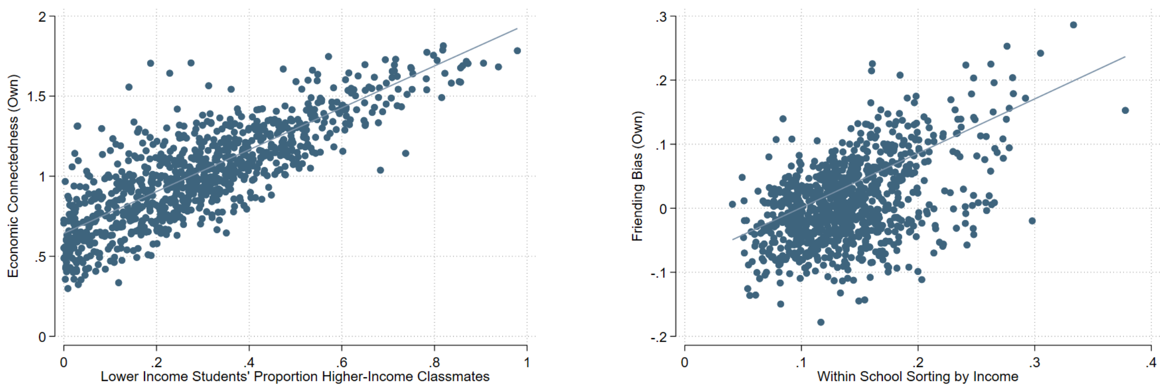
Notes: Both the number of schools to students and the variance ratio are standardized based on the school-to-student distribution and variance ratio in a district, weighted by the number of students enrolled and calculated within the grade group. Schools are placed into districts, and the ratio is calculated as the number of schools in the district to the number of students served in the district in 2019. The number of private schools, number of students and number of grades served in each private school are based on the Texas Alliances Accredited Private Commission archive data for the 2018–2019 school year. The "univariate" estimate is based on regressing the variance ratio on the standardized number of schools to students. The "demographic controls" estimate is based on regressing the variance ratio on the standardized number of schools to students, with controls for the proportion of Black, Hispanic and higher-income students in the district.

Figure 11: Within-School Sorting Correlates More with the Number of Science and Math Courses than Advanced Courses



Notes: Based on 2019 high school classroom enrollment data. The first row captures the school-level univariate regression coefficient from regressing the standardized sorting measure on the standardized number of courses offered to students served. The other rows capture the correlation with other specific groups of courses to students served. Math courses capture the number of any math course to the number of students served, standardized. Math (not advanced) courses capture all math courses that are not advanced to the number of students served. The standardization is based on the weighted distribution of courses to students and within-school sorting across schools. The correlation is weighted by the number of students enrolled in a school. The 95% confidence intervals are presented. The standard errors are clustered at the school level.

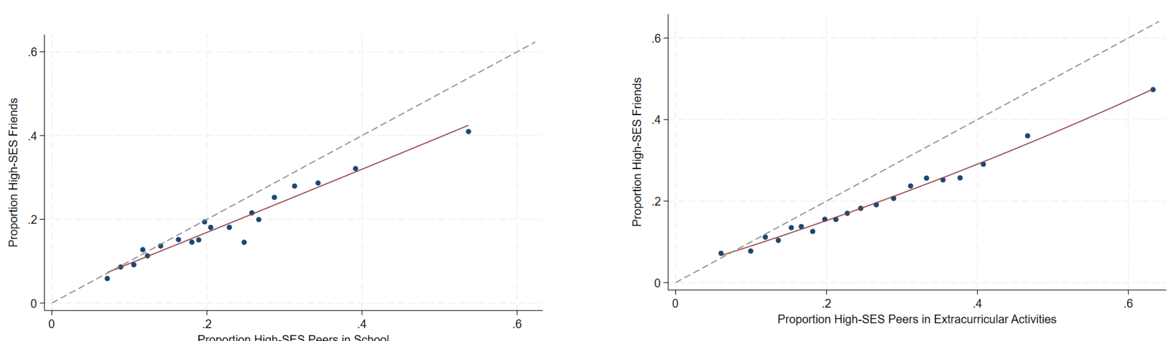
Figure 12: Strong Relationship between Likelihood of Befriending Higher-Income Students and Classroom Exposure



(a) Classroom Exposure and Economic Connectedness (b) Classroom Sorting by Income and Friending Bias

Notes: Each dot represents a school. I was able to link 1132 high schools to the friendship formation high school measures in Chetty et al. (2022). Of the 1132 schools, 981 have data on economic connectedness. I merged the two datasets with school name and district information. The fitted line weights schools by number of students enrolled. Panel (a) presents the correlation between high school measures of economic connectedness as captured by Chetty et al. (2022) and the proportion of higher-income students to whom lower-income students are exposed in each high school in 2012. Economic connectedness captures the likelihood of befriending a higher-income individual on Facebook. Panel (b) presents the correlation between high school measures of friending bias as captured by Chetty et al. (2022) and the difference in the proportion of higher-income students in higher- and lower-income students' classrooms, within a school (variance ratio). The variance ratio is based on 2012 student enrollment data. Friending bias captures the likelihood of befriending a higher-income individual on Facebook, conditional on the school proportion of higher-income students.

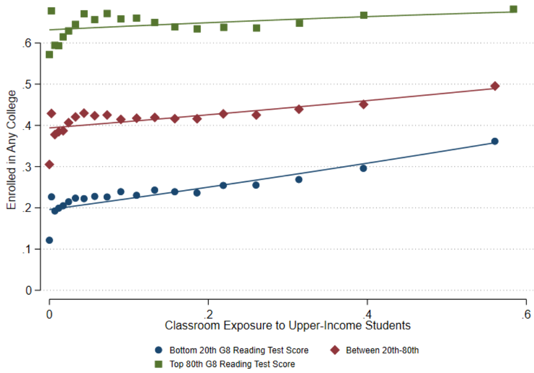
Figure 13: Strong Relationship Between Students' School and Extracurricular Composition and Friendship Pattern



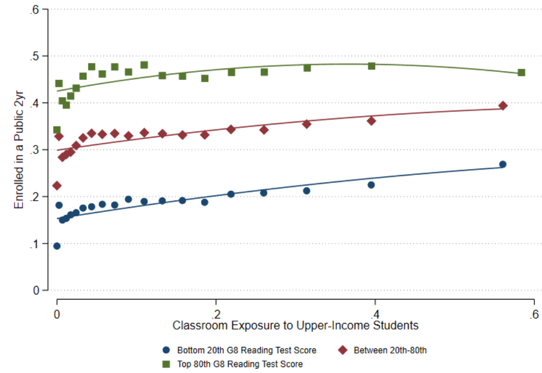
(a) Proportion of High-SES Peers in School (b) Proportion of High-SES Peers in School Extracurricular Activities

Notes: The definition of high-SES is described in Section 3.2. The binned scatter plots are based on the full sample of low-SES students with data on friendship patterns. The bins are based on grouping the x-values into 20 equal-sized bins. Then, it computes the average y-variable value for each bin. The fitted lines are weighted by survey sampling weights. Panel (a) captures the relationship between a student's proportion of high-SES peers in school and their proportion of high-SES friends. Panel (b) captures the relationship between a student's proportion of high-SES peers in their school-listed extracurricular activities and their proportion of high-SES friends. In both panels, the dashed line is a 45-degree line representing a 1-to-1 relationship between the average proportion of high-SES students in school/extracurriculars and the average proportion of high-SES friends.

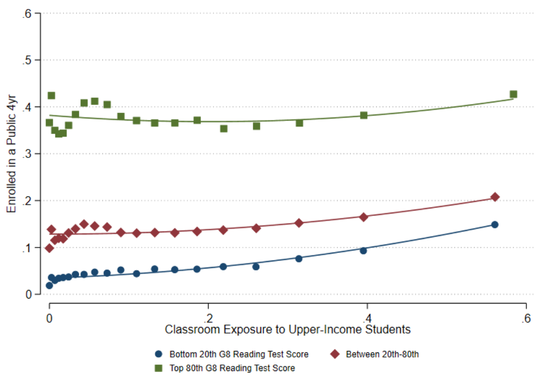
Figure 14: Exposure to Higher-Income Students, College Enrollment and Employment



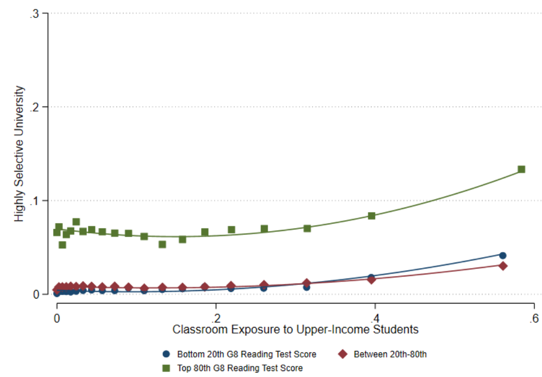
(a) Enrolled in Any College



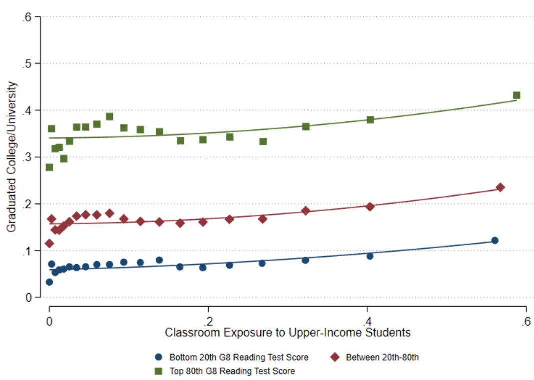
(b) Enrolled in 2-year Public College



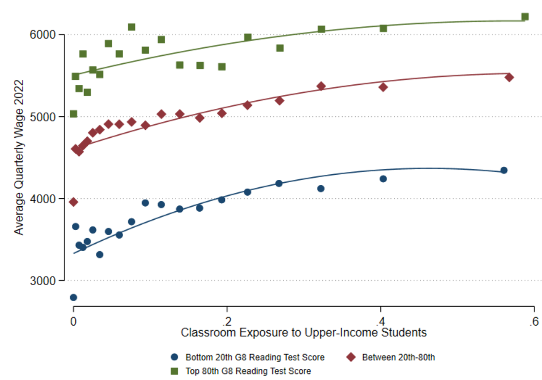
(c) Enrolled in 4-year Public University



(d) Enrolled in Highly Selective University



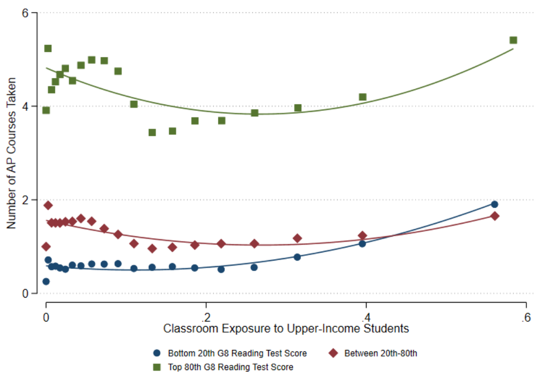
(e) Graduated from Any College/University



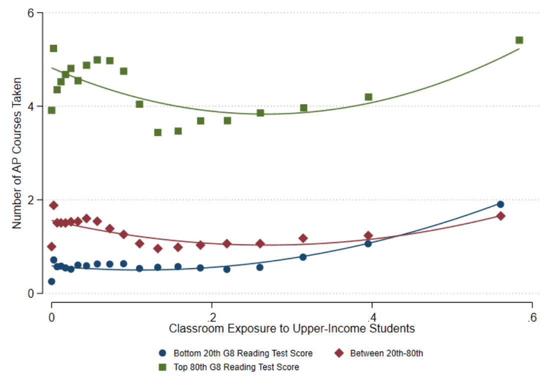
(f) Average Quarterly Wage in 2022 (Age 23-26)

Notes: The fitted quadratic line is based on the relationship between students' classroom exposure to upper-income classmates on the various outcomes, weighted by the number of students enrolled in each subgroup. College enrollment outcomes include cohorts 2011 to 2016. College graduation and wage outcomes include cohorts 2011 to 2014. The bins are based on grouping the x-values into 20 equal-sized bins. Then, it computes the average y-variable value for each bin.

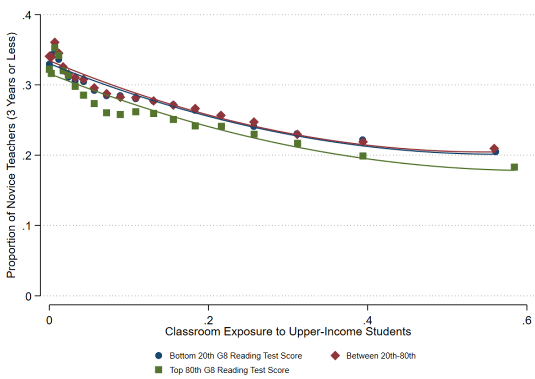
Figure 15: Exposure to Higher-Income Students and School Resources



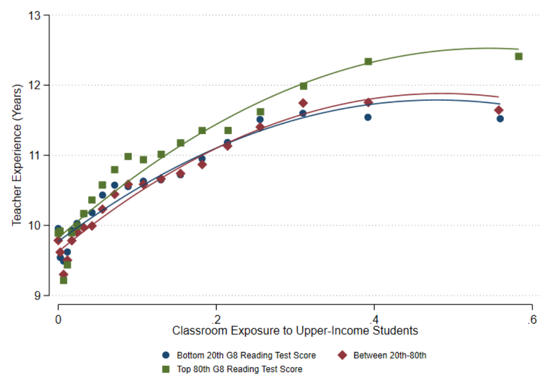
(a) Number of AP Courses Enrolled in



(b) Number of Advanced Courses Enrolled in



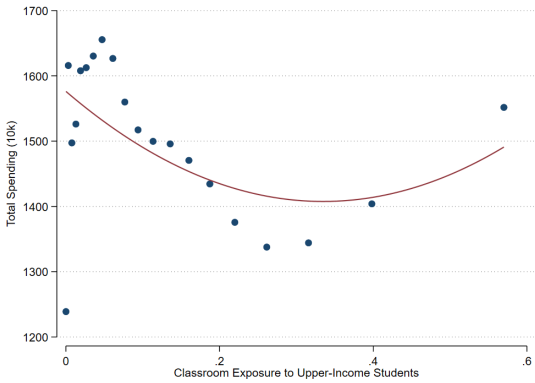
(c) Proportion of Novice Teachers



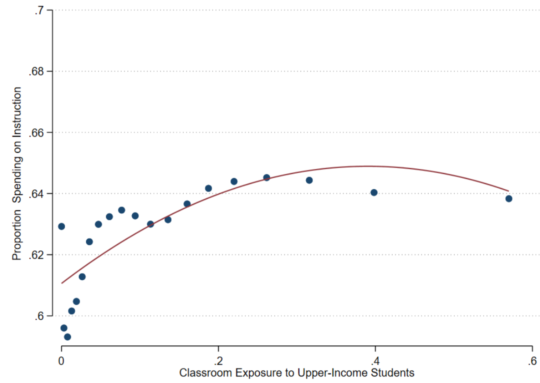
(d) Years of Teacher Experience

Notes: The line and plots are similar to those in Figure (14). AP and advanced course enrollments are based on the average number of AP courses taken by the student during high school. The course enrollment outcomes include cohorts 2011 to 2016. The proportion of novice teachers is based on the proportion of full-time teachers with three or less years of experience that taught in a student's classroom in high school. Teacher data include cohorts 2012 to 2016.

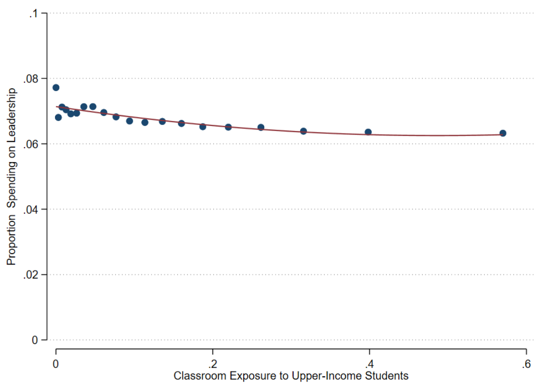
Figure 16: Exposure to Higher-Income Students and School Spending per Pupil



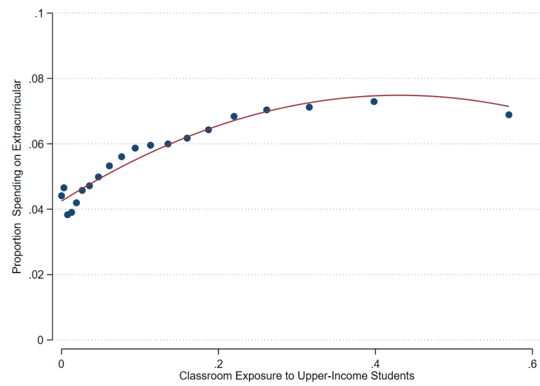
(a) Average School Spending per Pupil



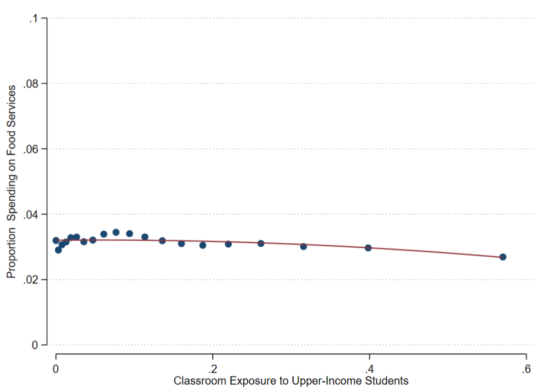
(b) Proportion of Total Spending on Instruction



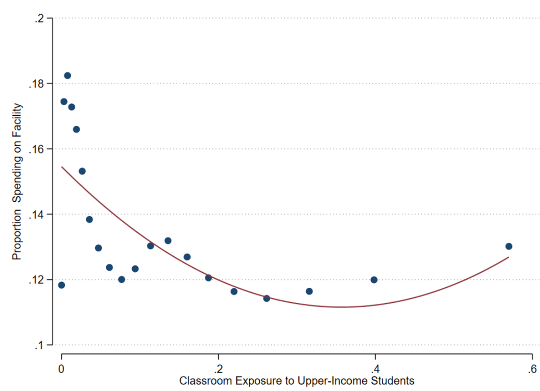
(c) Proportion of Total Spending on School Counselors



(d) Proportion of Total Spending on Co-/Extracurriculars



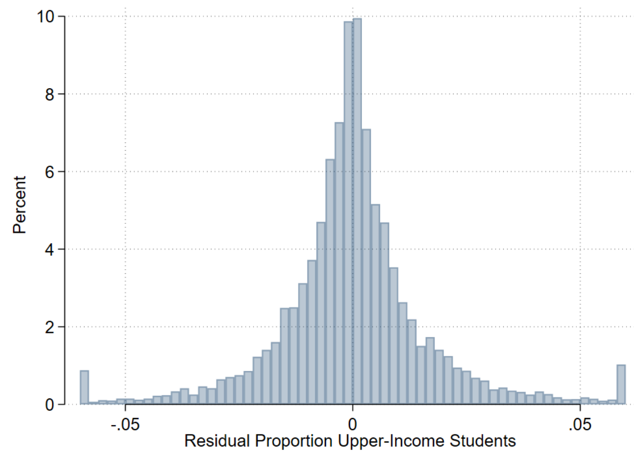
(e) Proportion of Total Spending on Food Services



(f) Proportion of Total Spending on Facilities

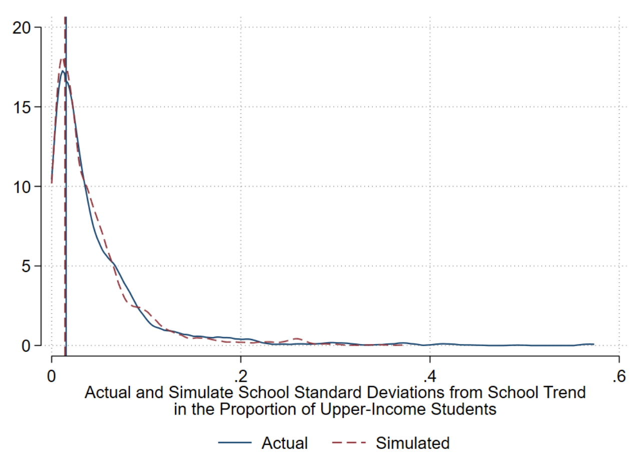
Notes: Spending is based on school actual spending data between 2012 and 2019 in each year divided by the total number of students enrolled in the school that year. Panel (a) captures the average yearly spending per pupil during the cohort's high-school years. Panels (b)–(f) capture the proportion of total spending on each category. The instruction category combines the following functions: instruction, instruction resources and media services, curriculum and staff development, and instructional leadership. Facilities combines the following functions: facility acquisition and construction and facility maintenance/operations. With the exception of food services, I only included categories that make up more than 4% of the budget, on average. The data include cohorts 2012 to 2016. The bins are based on grouping the x-values into 20 equal-sized bins. Then, it computes the average y-variable value for each bin.

Figure 17: Distribution of Residual Variation in Proportion Upper-Income Students



Notes: The histogram presents the variation in the proportion of upper-income students based on the residual from a regression with school and cohort fixed effects, as well as school time trends.

Figure 18: Simulated and Actual Distribution of within School Standard Deviations from School Trend



Notes: The figure captures the distribution of each school's standard deviation in the proportion of upper-income students from school trend (solid line) and each school's simulated average standard deviations in the proportion of upper-income students from school mean (dashed line). The vertical lines capture each distributions' median standard deviation in the proportion of upper-income students.

10 Supplementary Appendix

10.1 Appendix A: Notes on Simulation Calculations

To calculate the expected exposure to higher-income students for each income group under various random assignment levels, excluding own status, I do the following. I calculate the expected number of (higher-income) peers in each classroom had students been randomly assigned to classrooms in unit j. To calculate the expected number of students in each classroom, I divide the total number of student-classroom enrollments in Texas state public schools in unit j in each year-cohort $TotalEnrollments_j$ by the total number of classrooms offered in unit j (N_j). To calculate the expected number of higher-income students, I calculate the total number of student-classroom enrollments for higher-income students in unit j in each year-cohort $TotalHighIncomeEnrollments_j$ and divide it by the total number of classrooms offered in unit j (H_j). The choice of unit j depends on the random assignment level (state/district/school). This is shown in Equation (3)).

$$\begin{aligned} H_j &= \frac{TotalHighIncomeEnrollments_j}{TotalClassrooms_j} \\ N_j &= \frac{TotalEnrollments_j}{TotalClassrooms_j} \end{aligned} \tag{3}$$

For each student, her expected proportion of higher-income peers had students been randomly assigned to classrooms in unit j is equal to the proportion of higher-income students in unit j, i.e., $\frac{H_j}{N_j}$ adjusted to exclude the student herself. To adjust the proportion to exclude a student's own status, if a student is a higher-income student, I subtract from both the denominator and numerator her number of classroom enrollments n_{ij} during a given year in unit j. If a student is lower-income, I subtract from the denominator only her number of classroom enrollments as shown in Equations (4)) and (5)).

$$ExposureRand_{Hj} = \frac{H_j - n_{ij}}{N_j - n_{ij}} \tag{4}$$

$$ExposureRand_{Lj} = \frac{H_j}{N_j - n_{ij}} \tag{5}$$

To calculate the cumulative expected exposure for a given student across expected grades, I calculate the average of her weighted proportion of higher-income classmates across the years. The weights are based on the number of classrooms a student is enrolled in each year.

10.2 Appendix B: Variance Ratio

To capture within-unit (district or school) sorting by income, conditional on the proportion of upper-income students, I use the variance ratio (also known as the captures the correlation ratio and eta squared). The variance ratio the difference (gap) in exposure to higher-income students between higher- and lower-income students. If students are randomly assigned to districts, schools, and classrooms, we should expect higher- and lower-income students to have the same average number of high-income students. The variance ratio builds on the exposure measure, with a system-wide composition adjustment, as shown in Equation (6). To maintain the variance ratio interpretation of the measure being equal to 0 if students are enrolled in the same classroom, in this calculation (as done in prior literature), I include students' own income status.

$$\begin{aligned} VarianceRatio_j &= \frac{E[Prophighincome_{ij}|H=1] - Prophighincome_j}{1 - Prophighincome_j} \\ &= E[Prophighincome_{ij}|H=1] - E[Prophighincome_{ij}|H=0] \end{aligned} \tag{6}$$

The variance ratio has a straightforward interpretation. In a perfectly integrated unit, the difference in exposure to higher-income students by income status would be equal to 0. In other words, everyone would be exposed to the same proportion of higher-income students in the school $Prophighincome_j$. In a perfectly segregated school, higher-income students would only be exposed to themselves $E[Prophighincome_{ij}|H = 1] = 1$, so the variance ratio would be equal to 1. Monarrez, Kisida and Chingos (2022) use the variance ratio to capture the impact of the expansion of charter schools on school segregation by race.

The variance ratio is sensitive to the unit's proportion of higher-income students: the size of the potential gap between groups differs by the units' composition (James and Taeuber, 1985). It is also sensitive to the number of classrooms/schools i within schools/districts j (Monarrez, Kisida and Chingos, 2022). A unit with more areas relative to the number of students has more scope for income sorting.

10.3 Appendix C: Segregation by Income and District School Offerings

To capture the relationship between school sorting and the number and type of schools offered, for each district, I calculate the number of schools that offer a given grade level and divide it by the number of students enrolled in that grade and district in 2019. Then, I run a regression with the number of schools to students on the level of between-school sorting as the outcome of interest. To capture school heterogeneity, I split schools into three types: traditional public schools, charter schools, and private schools.[71] I only observe students enrolled in public schools (traditional and charter), and so in the case of private schools, I examine the relationship between the number of private schools and sorting between public schools. Private schools provide higher-income students with an outside option. In doing so, they can alter both the peer composition of public schools and the policies and offerings of public schools. For simplicity, I focus on students enrolled in public schools (both traditional and charter) in the 2019 academic year in Texas.

Estimates of the relationship between the ratio of schools offered and the level of sorting by income is shown in Figure 10, with and without demographic controls. The errors are clustered at the district level and the estimates are weighted by the number of students enrolled.

The number of school options can also impact the level of within-school sorting by increasing competition for upper-income (or higher-achieving) students. Theoretically, public schools can use tracking to retain higher-performing students (Epple, Newlon, and Romano, 2002). Under tracking, higher-income students may be less likely to leave public schools to attend private schools. Figlio and Page (2002) find that higher-performing students are more likely to select into tracked schools. Similarly, Domina et al. (2017) find that schools with more advantaged students are more likely to increase tracking in response to policy pressures. As such, I run the same regression with within-school sorting as the outcome instead of between-school sorting. I find no evidence that within-school sorting in public schools is higher when the ratio of private schools to students is higher. There seems to be some evidence of a slightly lower level of within-school sorting in districts with more charter schools. These patterns are shown in Figure A29. Charter schools generally seem to have lower levels of within-school sorting, as shown in Table A4.

[71]The number of private schools in the district is based on the list of schools in 2018–2019 published by the Texas Private School Accreditation Commission. This list includes the number of students enrolled in each school and the grades served by the school. However, I do not know the number of students served in each grade or their demographics. I estimate the number of students in each grade by assuming that the same number of students are served in each grade. The within- and between-school sorting measures are based on students enrolled in public schools only.

10.4 Appendix D: Add Health Data and Income Measure

The at-home survey has information on parental income but only for a random subsample of students from the wider in-school survey. Therefore, I use the socioeconomic variables available for all students to build a model that predicts student income to capture all student SESs who share the same school extracurricular. I use a simple linear regression and use the following variables to predict student income: Father and Mother's occupation, Father and Mother's education, Father and Mother's employment status, number of individuals in the household, and missing indicators. I tested and built this model within the subset of students who were surveyed at home for whom I have income data. Then, I used this model to predict the income for the entire sample of students with the in-school survey. The students were then divided into three income groups based on their predicted income that mimic the income group sizes in the Texas data. High-SES students are those whose predicted income is in the top 24 percentiles, and low-SES students are students whose predicted income is in the bottom 29 percentiles. These three income indicators seem to effectively capture the variation in parental income. The median income is 26.6, 40.4 and 67.7 thousand dollars for low-, middle-, and high-SES students, respectively.[72] I summarize the characteristics of each of the income groups (including parental education) in Table 10.5.

The Add Health data list 33 extracurricular activities that students can check. The extracurricular activities listed are the following: yearbook, student council, honor society, newspaper, wrestling, volleyball, track, tennis, swimming, soccer, ice hockey, football, field hockey, basketball, baseball/softball, other sport, orchestra, chorus or choir, cheerleading/dance team, band, science club, math club, history club, Future Farmers of America, drama club, debate team, computer club, book club, Spanish club, Latin club, German club, French club, other club or organization.

[72]The median is based on the full sample of students in the at-home survey for whom I have parental income data. I list these in 1994 dollars, which are equivalent to 46.45, 70.5 and 118.21 thousand 2020 dollars. I split the set of students surveyed at home into two equally sized random groups. The in-sample half is used to build the model, and the out-of-sample half is used to test the model. The average income for out-of-sample high-SES students surveyed at home is 68.6 thousand dollars.

10.5 Appendix E: Tables and Figures

Table A1: Add Health Student Summary Statistics

Variable	Mean
Hispanic	0.1190
White	0.5952
Black	0.2034
Either Parent with College Degree	0.3632
Either Parent in Prof. Occupation	0.4444
Parental Income	43.1524
Median Income	35.0000
Proportion High-SES	0.2416
Proportion Low-SES	0.2872
Number of Students	85627
Number of Schools	142

Notes. This table summarizes demographic statistics for students surveyed in the Add Health in-school surveys. The variables "Median Income" and "Parental Income" are based on the at-home surveys of a random subset of students (17,238) for whom there are income data. The high- and low-SES indicators are based on the predicted income measure described in Section 3.2. All averages are weighted by survey sampling weights to be nationally representative.

Table A2: Add Health Student Summary Statistics by Income Group

Variable	Low-SES	Mid-SES	High-SES
Hispanic	0.1686	0.1175	0.0630
White	0.4105	0.6354	0.7362
Black	0.3183	0.1763	0.1198
Either Parent with College	0.0601	0.2718	0.8014
Either Parent in Prof. Occupation	0.1332	0.3569	0.8443
Proportion High-SES Friends	0.1715	0.2371	0.4034
Proportion High-SES in Extracurricular	0.2349	0.2734	0.3888
Proportion High-SES in School	0.1956	0.2276	0.3237
Number of Extracurriculars	1.9098	2.1660	2.8513
Deviation of Extracurricular from School Prop High-SES	0.0363	0.0435	0.0586
Parental Income (Thousands of Dollars)	26.6107	40.4065	67.7105
Median Income (Thousands of Dollars)	20.0000	36.0000	55.0000
Number of Students	23800	38961	22866

Notes. This table summarizes demographic statistics for students surveyed in the Add Health in-school surveys. The variables "Median Income" and "Parental Income" are based on the at-home surveys of a random subset of students (17,238) for whom there are income data. The high- and low-SES indicators are based on the predicted income measure described in Section 3.2. All averages are weighted by survey sampling weights to be nationally representative.

Table A3: Student School and Classroom Enrollment by Expected Grade

Variable	5	6	7	8	9	10	11	12
Enrolled in Charter School	.037	.057	.058	.06	.054	.058	.057	.053
	(.188)	(.232)	(.235)	(.238)	(.226)	(.235)	(.233)	(.224)
Enrolled in Alternative School	.006	.009	.011	.015	.024	.036	.045	.042
	(.08)	(.094)	(.105)	(.122)	(.153)	(.187)	(.207)	(.2)
Enrolled in Title 1 School	.706	.612	.568	.57	.418	.413	.421	.435
	(.455)	(.487)	(.495)	(.495)	(.493)	(.492)	(.494)	(.496)
Special Education	.089	.091	.09	.089	.087	.085	.083	.083
	(.285)	(.288)	(.286)	(.284)	(.281)	(.279)	(.276)	(.275)
Gifted Program	.094	.097	.099	.099	.096	.095	.098	.105
	(.292)	(.296)	(.298)	(.299)	(.294)	(.294)	(.298)	(.306)
Enrolled in Bilingual Program	.171	.08	.069	.071	.075	.078	.063	.035
	(.377)	(.271)	(.254)	(.256)	(.263)	(.268)	(.244)	(.185)
Number of Advanced Courses Taken	0	0	.001	.026	.332	.69	1.721	1.675
	(0)	(.006)	(.041)	(.237)	(.804)	(1.345)	(2.709)	(2.264)
Number of Classrooms	9.889	9.396	9.70	10.077	14.767	14.861	12.095	8.481
	(3.968)	(3.764)	(3.688)	(3.5)	(3.148)	(3.214)	(4.595)	(4.308)
Number of Courses Taken	9.277	8.632	8.806	9.288	14.167	14.333	11.695	8.232
	(3.615)	(3.32)	(3.248)	(3.112)	(2.823)	(2.868)	(4.179)	(3.906)
Any Vocational Ed	.055	.081	.207	.377	.691	.797	.832	.842
	(.229)	(.273)	(.405)	(.485)	(.462)	(.402)	(.374)	(.365)
Number of Students	1124550	1093343	1076510	1064386	1052391	1035723	988132	905982

Notes. This table describes average enrollment across three cohorts of students followed from grade 5 to 12 from 2012 to 2021 in each type of school each year as well as a description of the course offerings in each type of school. The number in brackets is the standard deviation from the mean.

Table A4: School Classroom and Course Offerings by Grade

Variable	5	6	7	8	9	10	11	12
Number of Classrooms	63.262	134.705	178.256	197.025	798.786	1001.428	909.196	615.465
	(46.286)	(83.599)	(106.223)	(119.956)	(458.365)	(528.681)	(583.499)	(454.558)
Number of Courses	10.387	17.052	24.806	31.569	137.994	208.034	232.223	193.952
	(4.177)	(7.503)	(11.134)	(12.549)	(55.622)	(78.966)	(112.296)	(106.083)
Number of Advanced Courses	0	.002	.018	.286	6.527	19.015	34.147	37.771
	(0)	(.065)	(.18)	(.749)	(5.351)	(12.55)	(22.686)	(24.838)
Number of CTE Courses	10.386	16.876	23.395	28.614	105.311	148.262	157.305	126.841
	(4.176)	(7.374)	(10.321)	(11.274)	(41.72)	(56.57)	(76.935)	(70.561)
Number of Students	144.171	285.171	314.366	315.854	556.76	510.18	479.562	445.829
	(112.186)	(149.742)	(149.736)	(153.836)	(314.335)	(289.425)	(284.642)	(268.138)
N. of Traditional Public Schools in District (weighted)	32.77	12.609	11.06	11.259	9.371	8.925	8.421	7.896
	(42.932)	(14.626)	(13.307)	(13.371)	(11.566)	(11.043)	(10.514)	(10.169)
N. of Traditional Public Schools in District (unweighted)	3.727	2.128	1.926	1.965	1.857	1.851	1.79	1.687
	(10.706)	(4.424)	(3.549)	(3.643)	(3.007)	(2.954)	(2.821)	(2.654)
Number of Schools	4263	2719	2423	2455	2309	2269	2206	2102
Number of Districts	1027	1023	1014	1013	981	979	979	979

Notes. This table summarizes the number and types of courses provided on average in schools serving students in the three cohorts in each grade level. Averages are weighted by the number of students served in each school. Numbers in brackets present the standard deviations from the mean. The average across cohorts in each grade level is based on the year a cohort is expected to be in that grade level.

Table A5: Gap in Exposure by District Type [NCES]

Type of District	(1) Prop LI	(2) Prop HI	(3) Exp LI to HI	(4) VR: btwn Schl	(5) VR: within Schl	(6) Exp Gap [in Dist]	(7) Exp Gap [in Schl]
City-Large	.364	.149	.056	.154	.07	.042	.005
City-Midsize	.295	.204	.09	.094	.086	.037	.009
City-Small	.348	.226	.108	.099	.101	.041	.011
Rural-Distant	.208	.258	.191	.003	.083	.009	.009
Rural-Fringe	.231	.287	.146	.021	.082	.016	.009
Rural-Remote	.255	.187	.149	.002	.083	.005	.005
Suburb-Large	.225	.304	.114	.102	.08	.047	.008
Suburb-Midsize	.243	.273	.144	.025	.087	.017	.01
Suburb-Small	.197	.263	.195	.073	.112	.063	.024
Town-Distant	.293	.157	.128	.005	.096	.011	.01
Town-Fringe	.259	.188	.132	.011	.085	.011	.01
Town-Remote	.331	.135	.103	.006	.098	.009	.009

Notes. Each column presents the variable average weighted by the number of students enrolled in each district type. District type is based on NCES categorization. Higher- and lower-income students are defined as students never and always on free/reduced lunch, respectively. Column (3) captures the average cumulative proportion of higher-income students in lower-income students' classrooms. Column (4) captures the variance ratio between schools in a district, which is the level of between-school sorting. Column (5) captures the variance ratio within a school, which is the level of within-school sorting. The variance ratio is the difference in the proportion of higher-income students in higher- relative to other-income students' schools (classrooms) in a distrct (school). Column (6) captures the difference between average exposure to higher-income students shown in Column (3) and expected exposure had students been randomized to schools and classrooms in the district. Column (7) captures the difference between average exposure to higher-income students shown in Column (3) and expected exposure had students been randomized to classrooms in the school. The numbers in brackets are the standard deviation from the mean.

Table A6: Gap in Exposure by District Type [TEA]

Type of District	(1) Prop LI	(2) Prop HI	(3) Exp LI to HI	(4) VR: btwn Schl	(5) VR: within Schl	(6) Exp Gap [in Dist]	(7) Exp Gap [in Schl]
Charter School Districts	.329	.116	.047	.052	.05	.017	.002
Independent Town	.315	.161	.124	.01	.109	.016	.013
Major Suburban	.211	.297	.123	.114	.084	.054	.009
Major Urban	.384	.128	.055	.193	.068	.048	.005
Non-metro Fast Growing	.171	.305	.242	.007	.076	.016	.009
Non-metro Stable	.281	.193	.121	.003	.087	.007	.007
Other Central City	.329	.231	.086	.097	.086	.038	.008
Other Central City Suburban	.282	.247	.116	.018	.082	.014	.009
Rural	.245	.201	.151	.003	.08	.005	.005

Notes. Each column presents the variable average weighted by the number of students enrolled in each district type. District type is based on the TEA categorization in the data. Higher- and lower-income students are defined as students never and always on free/reduced lunch, respectively. Column (3) captures the average cumulative proportion of higher-income students in lower-income students' classrooms. Column (4) captures the variance ratio between schools in a district, which is the level of between-school sorting. Column (5) captures the variance ratio within a school, which is the level of within-school sorting. The variance ratio is the difference in the proportion of higher-income students in higher- relative to other-income students' schools (classrooms) in a distrct (school). Column (6) captures the difference between average exposure to higher-income students shown in Column (3) and expected exposure had students been randomized to schools and classrooms in the district. Column (7) captures the difference between average exposure to higher-income students shown in Column (3) and expected exposure had students been randomized to classrooms in the school. The numbers in brackets are the standard deviation from the mean.

Table A7: Grade 3-8 Average Standardized Reading Scores for 9th Graders

Cohort	% Missing	All	High-Income	Low-Income	High-Achieve
2010	4.1	-.084	.361	-.396	.585
2011	4.4	-.059	.387	-.37	.608
2012	3.9	-.104	.385	-.421	.627
2013	4	-.069	.448	-.38	.746
2014	5.8	-.055	.401	-.325	.712
2015	5	-.065	.393	-.333	.729
2016	4.5	-.111	.408	-.396	.802

Table A8: Correlation Between Proportion Upper-Income Students in High-School and Lower-Income Students' Demographic Characteristics

	Proportion Upper-Income Students
Black Student	-0.0158
	(0.0158)
Group Mean	0.15
N Clusters	2141
N	1013905
White Student	0.0250
	(0.0171)
Group Mean	0.09
N Clusters	2141
N	1013905
Hispanic Student	-0.00684
	(0.0225)
Group Mean	0.68
N Clusters	2141
N	1013905
Ever Immigrant	-0.01474
	(0.0133)
Group Mean	0.10
N Clusters	2141
N	1013905
Female Student	-0.0101
	(0.0246)
Group Mean	0.47
N Clusters	2141
N	1013905
Income Reported on FAD	-0.931
	(4.434)
Group Mean	28.92
N Clusters	1926
N	298598

Standard errors clustered at the school level in parentheses. Each coefficient is based on a regression of the variable on the proportion upper-income students, including school and cohort fixed effects, and school time trends. Ever immigrant is based on if a students was ever assigned an immigrant status in the Texas data. A student is labeled as immigrant in the data if they were not born in any state and have not attended any state for more than three academic years.

Table A9: Impact of an Increase in the Proportion of Upper-Income Students on Classroom Proportion Upper-Income Classmates for Lower-Income Students

	(1)	(2)
Proportion Upper-Income	0.564	0.578
	(0.00861)	(0.00818)
Proportion Upper-IncomeXTop G8 Test Score		0.126
		(0.00513)
Proportion Upper-IncomeXLow G8 Test Score		-0.0702
		(0.00336)
N Clusters	2103	2094
N	882034	805717

Standard errors are in parentheses and clustered at the school level. Coefficients are based on Equation (1). The regressions include the full sample of lower-income students. The second model includes an interaction with students who scored in the top 80th percentile and bottom 20th percentile based on their grade 8 reading test scores. Models include cohorts 2011–2016 because classroom data are only available starting 2011. The outcome is a student's classroom proportion of high-income peers. The regression is based on lower-income students.

Table A10: Impact of an Increase in the Proportion of Higher-Income Students on Employment Industry for Lower-Income Students

	(1) Construction	(2) Information	(3) Finance	(4) Prof. Science	(5) Education
Proportion Upper-Income	0.00157	-0.00707	-0.0137	0.00893	0.00373
	(0.0146)	(0.00577)	(0.00986)	(0.0115)	(0.0120)
N Clusters	1992	1992	1992	1992	1992
N	700245	700245	700245	700245	700245

Standard errors are in parentheses and clustered at the school level. The coefficients are based on Equation (1). The models include cohorts 2010–2014.

Table A11: Impact of an Increase in the Proportion of Upper-Income Students on Lower-Income Students: By Student Test Score

	(1) Any College	(2) 2yr Public	(3) 4yr Public	(4) Selective	(5) Grad Any	(6) Wage 2022	(7) Income Percentile
Proportion Upper-Income	0.0288	0.0366	0.0319	0.000608	-0.000156	799.2	3.883
	(0.0262)	(0.0264)	(0.0203)	(0.00627)	(0.00843)	(391.4)	(1.721)
Proportion Upper-IncomeXTop G8 Test Score	-0.000384	0.00561	-0.0829	0.00506	0.00736	-28.98	-1.618
	(0.0153)	(0.0198)	(0.0170)	(0.00849)	(0.00913)	(193.9)	(0.814)
Proportion Upper-IncomeXLow G8 Test Score	0.0558	0.0141	0.0452	0.00370	-0.000569	-40.11	1.603
	(0.0163)	(0.0135)	(0.0137)	(0.00243)	(0.00238)	(131.7)	(0.631)
N Clusters	2132	2132	2132	2132	1989	1989	1989
N	925930	925930	925930	925930	638590	638590	638590

Standard errors are in parentheses and clustered at the school level. Coefficients are based on Equation (1) with student own test score interactions. The models include an interaction with students who scored in the top 80th percentile and bottom 20th percentile on their grade 8 test scores. The regression is limited to lower-income students with grade 8 test-scores. Models (1)–(4) include cohorts 2010–2016. Models (5)–(7) include cohorts 2010–2014.

Table A12: Impact of an Increase in the Proportion of Higher-Income Students on a Cohort's Racial/Ethnic Composition

	(1) Prop. Hispanic	(2) Prop. Black	(3) Prop. White
Proportion Upper-Income	-0.243	-0.0567	0.322
	(0.0155)	(0.00934)	(0.0150)
N Clusters	2141	2141	2141
N	1013905	1013905	1013905

Standard errors are in parentheses and clustered at the school level. The coefficients are based on Equation (1). Models include cohorts 2010–2016.

Table A13: Impact of Proportion Upper-Income and High-Achieving Students on College Enrollment for Lower-Income Students

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Enrolled in College/University						
Proportion Upper-Income	0.0795		0.108	0.0455		0.0640
	(0.0240)		(0.0246)	(0.0246)		(0.0249)
Proportion High-Achieve		-0.0869	-0.0986		-0.0802	-0.0854
		(0.0210)	(0.0212)		(0.0207)	(0.0208)
Group Mean	0.380					
Enrolled in a Public 2yr College						
Proportion Upper-Income	0.0854		0.105	0.0374		0.0517
	(0.0251)		(0.0263)	(0.0244)		(0.0253)
Proportion High-Achieve		-0.0568	-0.0682		-0.0619	-0.0661
		(0.0198)	(0.0203)		(0.0201)	(0.0205)
Group Mean	0.290					
Enrolled in a Public 4yr College						
Proportion Upper-Income	0.0411		0.0542	0.0379		0.0479
	(0.0165)		(0.0163)	(0.0193)		(0.0194)
Proportion High-Achieve		-0.0401	-0.0460		-0.0422	-0.0461
		(0.0148)	(0.0148)		(0.0159)	(0.0159)
Group Mean	0.140					
Enrolled in a Selective University						
Proportion Upper-Income	0.00557		0.00892	0.00305		0.00568
	(0.00465)		(0.00474)	(0.00580)		(0.00590)
Proportion High-Achieve		-0.0108	-0.0118		-0.0117	-0.0122
		(0.00397)	(0.00402)		(0.00454)	(0.00460)
Group Mean	0.0200					
School Time Trends				X	X	X
N	1013905	1013905	1013905	1013905	1013905	1013905
N Clusters	2141	2141	2141	2141	2141	2141

Standard errors are in parentheses and clustered at the school level. Coefficients are based on Equation (1). Models (1)–(3) do not include school time trends. College enrollment outcomes include cohorts 2010–2016. Models (3) and (6) include both the proportion of upper-income and higher-achieving peers in the cohort. Group Mean is the average for lower-income students in the sample.

Table A14: Impact of Proportion Upper-Income and High-Achieving Students on College Graduation and Wages for Lower-Income Students

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Graduated College/University						
Proportion Upper-Income	0.0552		0.0589	0.0272		0.0308
	(0.0206)		(0.0206)	(0.0226)		(0.0227)
Proportion High-Achieve		-0.00534	-0.0125		-0.0124	-0.0154
		(0.0175)	(0.0176)		(0.0173)	(0.0174)
Group Mean	0.160					
Average Quarterly Wage 2022						
Proportion Upper-Income	614.8		678.8	778.5		894.1
	(323.7)		(326.5)	(398.4)		(401.5)
Proportion High-Achieve		-139.4	-222.6		-415.6	-502.8
		(223.4)	(224.7)		(250.7)	(251.9)
Group Mean	4642.8					
Income Percentile 2022						
Proportion Upper-Income	1.399		2.184	3.300		3.745
	(1.380)		(1.401)	(1.648)		(1.664)
Proportion High-Achieve		-2.462	-2.730		-1.572	-1.938
		(1.019)	(1.028)		(1.075)	(1.080)
Group Mean	46.80					
School Time Trends				X	X	X
N	700245	700245	700245	700245	700245	700245
N Clusters	1992	1992	1992	1992	1992	1992

Standard errors are in parentheses and clustered at the school level. Coefficients are based on Equation (1). Models (3) and (6) include both the proportion of upper-income and higher-achieving peers in the cohort. College graduation and wages include cohorts 2010–2014. Group Mean is the average for lower-income students in the sample.

Table A15: Impact of Proportion Upper-Income Conditional on Peer Achievement: Sensitivity to Measure of Achievement

	Model 1	Model 2	Model 3	Model 4	Model 5
Enrolled in College/University					
Proportion Upper-Income	0.0678	0.0787	0.0677	0.0516	0.0564
	(0.0243)	(0.0240)	(0.0250)	(0.0240)	(0.0246)
Group Mean	0.380				
Enrolled in a Public 2yr College					
Proportion Upper-Income	0.0543	0.0600	0.0532	0.0422	0.0454
	(0.0241)	(0.0242)	(0.0257)	(0.0245)	(0.0247)
Group Mean	0.290				
Enrolled in a Public 4yr College					
Proportion Upper-Income	0.0520	0.0613	0.0528	0.0377	0.0453
	(0.0192)	(0.0188)	(0.0195)	(0.0185)	(0.0194)
Group Mean	0.140				
Enrolled in a Selective University					
Proportion Upper-Income	0.00571	0.00767	0.00685	0.00401	0.00432
	(0.00587)	(0.00580)	(0.00595)	(0.00584)	(0.00585)
Group Mean	0.0200				
Graduated College/University					
Proportion Upper-Income	0.0450	0.0462	0.0321	0.0358	0.0320
	(0.0223)	(0.0222)	(0.0228)	(0.0223)	(0.0226)
Group Mean	0.160				
Average Quarterly Wage 2022					
Proportion Upper-Income	1008.4	1011.7	894.1	1057.0	836.5
	(395.9)	(394.4)	(396.7)	(402.0)	(399.2)
Group Mean	4642.8				
Income Percentile 2022					
Proportion Upper-Income	4.079	4.125	3.815	4.609	3.647
	(1.653)	(1.657)	(1.675)	(1.680)	(1.657)
Group Mean	46.8				
Proportion High-Achieving (Math G8)	X				
Proportion High-Achieving (Math+Reading G8)		X			
Proportion High-Achieving (Reading G3-G8)			X		
Proportion High-Achieving (Reading G3)				X	
Peer Average Std. Test Score (Reading G8)					X

Standard errors are in parentheses and clustered at the school level. Coefficients are based on Equation (1). College enrollment outcomes include cohorts 2010–2016 (N: 1013905; N Clusters: 2141). College graduation and wages include cohorts 2010–2015 (N: 700245; N Clusters: 1992). All models include both a peer achievement control. The measure of achievement varies across models. Models (1)–(4) include a control for the proportion high-achieving peers where high-achieving students are those who score in the top 25 percentiles of the standardized test score distribution. Model (4) I control for students' own grade 3 reading and math test-scores instead of grade 8. Model (5) controls for a continuous measure of average grade 8 reading scores for all students. Group Mean is the average for lower-income students in the sample.

Table A16: Impact of an Increase in the Proportion of Upper-Income Students on Lower-Income Students, Conditional on Racial/Ethnic Composition

	(1) Any College	(2) 2yr Public	(3) 4yr Public	(4) Selective	(5) Grad Any	(6) Wage 2022	(7) Income Percentile
[1em] Proportion Upper-Income	0.0497	0.0367	0.0437	0.00410	0.0281	838.8	3.204
	(0.0252)	(0.0252)	(0.0199)	(0.00588)	(0.0232)	(413.4)	(1.697)
Proportion Hispanic Students	0.0280	0.0134	0.0279	0.00305	0.00962	264.9	0.0842
	(0.0219)	(0.0205)	(0.0142)	(0.00383)	(0.0162)	(275.7)	(1.219)
Proportion Black Students	-0.0449	-0.0701	-0.0174	0.00548	-0.0299	-111.4	-2.269
	(0.0334)	(0.0305)	(0.0238)	(0.00638)	(0.0238)	(432.4)	(1.820)
N Clusters	2141	2141	2141	2141	1992	1992	1992
N	1013905	1013905	1013905	1013905	700245	700245	700245

Standard errors are in parentheses and clustered at the school level. The coefficients are based on Equation (2) but interacted with the proportion of Hispanic and Black students instead. Models (1)–(4) include cohorts 2010–2016. Models (5)–(7) include cohorts 2010–2014.

Table A17: Impact of an Increase in the Proportion of Higher-Income Students on Lower-Income Students within a Racial/Ethnic Group: Hispanic Students

	(1) Any College	(2) 2yr Public	(3) 4yr Public	(4) Selective	(5) Grad Any	(6) Wage 2022	(7) Income Percentile
Proportion Upper-Income Hispanic Students	0.0755	0.0165	0.0327	0.0211	0.0701	1067.9	2.980
	(0.0711)	(0.0793)	(0.0664)	(0.0168)	(0.0682)	(952.5)	(4.065)
N Clusters	2013	2013	2013	2013	1885	1885	1885
N	688557	688557	688557	688557	475618	475618	475618

Standard errors are in parentheses and clustered at the school level. The coefficients are based on Equation (1). Models (1)–(4) include cohorts 2010–2016. Models (5)–(7) include cohorts 2010–2014. The sample is limited to Hispanic lower-income students.

Table A18: Impact of an Increase in the Proportion of Higher-Income Students on Lower-Income students within a Racial/Ethnic Group: White students

	(1) Any College	(2) 2yr Public	(3) 4yr Public	(4) Selective	(5) Grad Any	(6) Wage 2022	(7) Income Percentile
Proportion Upper-Income White Students	0.0747	0.0643	0.0257	0.0135	-0.00389	1962.6	13.12
	(0.0508)	(0.0479)	(0.0339)	(0.0106)	(0.0445)	(804.4)	(3.674)
N Clusters	1796	1796	1796	1796	1668	1668	1668
N	88135	88135	88135	88135	60843	60843	60843

Standard errors are in parentheses and clustered at the school level. The coefficients are based on Equation (1). Models (1)–(4) include cohorts 2010–2016. Models (5)–(7) include cohorts 2010–2014. The sample is limited to White lower-income students.

Table A19: Impact of an Increase in the Proportion of Higher-Income Students on Lower-Income Students within a Raci
Students

	(1) Any College	(2) 2yr Public	(3) 4yr Public	(4) Selective	(5) Grad Any	(6) Wage 2022
Proportion Upper-Income Black Students	-0.185	-0.240	0.429	0.0216	0.181	5631.2
	(0.195)	(0.178)	(0.160)	(0.0466)	(0.179)	(6198.7)
N Clusters	1535	1535	1535	1535	1390	1390
N	154185	154185	154185	154185	106733	106733

Standard errors are in parentheses and clustered at the school level. The coefficients are based on Equation (1). Models (1)–(4) include coho
include cohorts 2010–2014. The sample is limited to Black lower-income students.

Table A20: Impact of Proportion of Upper-Income, Holding Constant Proportion Mid-Income Students: on Lower-I

	(1) Any College	(2) 2yr Public	(3) 4yr Public	(4) Selective	(5) Grad Any	(6) Wage 2022	Inco
Proportion Upper-Income	0.0240	0.0256	0.00887	0.00244	0.0236	984.9	
	(0.0268)	(0.0266)	(0.0216)	(0.00634)	(0.0253)	(416.5)	
Proportion Middle-Income	-0.0403	-0.0222	-0.0545	-0.00114	-0.00662	374.2	
	(0.0189)	(0.0191)	(0.0153)	(0.00408)	(0.0178)	(243.2)	
Group Mean	0.380	0.290	0.140	0.0200	0.160	4642.8	
N Clusters	2141	2141	2141	2141	1992	1992	
N	1013905	1013905	1013905	1013905	700245	700245	

Table A21: Indirect Impact of the Proportion of Upper-Income Students: College Enrollment and Employment

	(1) Any College	(2) 2yr Public	(3) 4yr Public	(4) Selective	(5) Grad Any	(6) Wage 2022	(7) Income Percentile
Proportion Upper-Income (S)	0.0922	0.0740	0.0434	0.00495	0.0376	398.9	1.578
	(0.0345)	(0.0356)	(0.0281)	(0.00841)	(0.0312)	(519.9)	(2.239)
Proportion Upper-Income District (-S)	0.00566	0.0163	-0.00396	-0.00200	-0.00903	163.3	0.582
	(0.0161)	(0.0154)	(0.0103)	(0.00362)	(0.0179)	(246.2)	(1.085)
N Clusters	1559	1559	1559	1559	1369	1369	1369
N	878484	878484	878484	878484	604829	604829	604829

Standard errors are in parentheses and clustered at the school level. controlling for the proportion upper-income students in district schools other than the one a student is enrolled in. The proportion of high-achieving students are those who scored in the top 24 percentiles of the grade 8 reading test score. Models (1)–(4) include cohorts 2010–2016. Models (5)–(7) include cohorts 2010–2014.

Table A22: Indirect Impact of the Proportion of Upper-Income Students: Resources

	(1) Classroom Exposure	(2) Class Sorting	(3) Teacher Experience	(4) Novice Teachers	(5) Spending	(6) Advanced	(7) AP
Proportion Upper-Income (S)	0.520	0.153	0.215	0.0186	-789.2	0.197	0.403
	(0.0132)	(0.0224)	(0.603)	(0.0367)	(807.2)	(0.503)	(0.345)
Proportion Upper-Income District (-S)	0.000650	-0.00392	-0.132	0.0177	611.9	0.0503	0.0906
	(0.00344)	(0.00763)	(0.233)	(0.0146)	(665.1)	(0.141)	(0.0909)
N Clusters	1518	1383	1391	1391	1218	1559	1559
N	767610	733464	642580	642580	620458	878484	878484

Standard errors are in parentheses and clustered at the school level. Controlling for the proportion upper-income students in district schools other than the one a student is enrolled in. Model (1) include cohorts 2011–2016 because the classroom data needed to calculate the within-school variance ratio are only available starting in 2011. Models (2)–(4) include cohorts 2012–2016 because teacher and school budget data linked to classrooms are only available starting in 2012. Models (5)–(6) include cohorts 2010-2016.

Table A23: Proportion Upper-Income and Average Quarterly Wage 2022

	Model 1	Model 2
Proportion Upper-Income	860.0	1102.4
	(110.2)	(99.08)
Group Mean	4642.8	4642.8
N Clusters	1995	1994
N	700248	699835
Cohort Fixed Effect	X	X
G8 School-Cohort Fixed Effect		X
District Fixed Effect		
School Fixed Effect		

Standard errors are in parentheses and clustered at the school level. Models include cohorts 2010-2014. Income for students without unemploym

Table A24: Impact of Increase in Proportion Upper-Income Students on Lower-Income Students: Excluding Outlier Observations (Limiting the Sample to School with Within School Standard Deviations less than 0.3pp)

	(1) Any College	(2) 2yr Public	(3) 4yr Public	(4) Selective	(5) Grad Any	(6) Wage 2022	(7) Income Percentile
Proportion Upper-Income	0.0451	0.0370	0.0378	0.00308	0.0272	756.2	3.169
	(0.0247)	(0.0246)	(0.0194)	(0.00583)	(0.0228)	(400.8)	(1.657)
N clusters	2129	2129	2129	2129	1981	1981	1981
N	1013816	1013816	1013816	1013816	700175	700175	700175

Standard errors are in parentheses and clustered at the school level. The coefficients are based on Equation (1) but without controlling for students grade 8 test and demographic characteristics. Models (1)–(4) include cohorts 2010–2016 and Models (5)–(7) include cohorts 2010–2014. Models exlude observations from schools with a standard deviation from school mean trend in the proportion of upper-income peers larger than 0.3pp.

Table A25: Proportion Upper-Income Peers and Lower-Income Students' Average Cohort Income

	Prop FAD	Parent Income (FAD)	Years FRPL	Prop FRPL
Proportion Upper-Income	0.247	52.83	-6.761	-0.791
	(0.0193)	(4.669)	(0.137)	(0.0146)
Group Mean	0.400	40.02	6.350	6.350
N	1013905	1011522	1013905	1013905
N clusters	2141	2080	2141	2141

Standard errors clustered at the school level in parentheses. Each coefficient is based on a regression of the variable on the proportion upper-income students, including school and cohort fixed effects, and school time trends. The outcomes capture a lower-income students' average cohort characteristics excluding own status. "Prop FAD" captures the proportion of a student's cohort who submitted their financial aid (FAD) applications. "Parent Income (FAD)" is the average cohorts' income based on students' reported parental income in their FAD application. Years FRPL captures a student's peers average number of years on free/reduced lunch and prop. FRPL captures a student's peers average proportion of years on free/reduced lunch.

Table A26: Impact of Proportion Upper-Income Students on Lower-Income Students' College Enrollment and wages: Robustness to Specification

	Model 1	Model 2	Model 3	Model 4	Model 5
Enrolled in College/University					
Proportion Upper-Income	0.116	0.0633	0.0665	0.0454	0.0538
	(0.0241)	(0.0250)	(0.0247)	(0.0246)	(0.0301)
Group Mean	0.380	0.380	0.380	0.380	0.380
N Clusters	2141	2141	2141	2141	2141
Enrolled in a Public 2yr College					
Proportion Upper-Income	0.113	0.0511	0.0531	0.0374	0.0120
	(0.0251)	(0.0248)	(0.0246)	(0.0245)	(0.0302)
Group Mean	0.290	0.290	0.290	0.290	0.290
N Clusters	2141	2141	2141	2141	2141
Enrolled in a Public 4yr College					
Proportion Upper-Income	0.0611	0.0482	0.0497	0.0379	0.0568
	(0.0163)	(0.0188)	(0.0187)	(0.0193)	(0.0228)
Group Mean	0.140	0.140	0.140	0.140	0.140
N Clusters	2141	2141	2141	2141	2141
Enrolled in a Selective University					
Proportion Upper-Income	0.00902	0.00481	0.00474	0.00304	0.00737
	(0.00467)	(0.00583)	(0.00582)	(0.00581)	(0.00728)
Group Mean	0.0200	0.0200	0.0200	0.0200	0.0200
N Clusters	2141	2141	2141	2141	2141
Graduated College/University					
Proportion Upper-Income	0.0614	0.0397	0.0400	0.0272	0.0238
	(0.0202)	(0.0223)	(0.0222)	(0.0227)	(0.0274)
Group Mean	0.140	0.140	0.140	0.140	0.140
N Clusters	1992	1992	1992	1992	1991
Average Quarterly Wage 2022					
Proportion Upper-Income	812.3	987.1	984.3	777.3	796.3
	(343.4)	(410.0)	(409.3)	(398.9)	(613.7)
Group Mean	4307.2	4307.2	4307.2	4307.2	4307.2
N Clusters	1992	1992	1992	1992	1991
Income Percentile 2022					
Proportion Upper-Income	2.501	4.298	4.308	3.297	2.926
	(1.459)	(1.720)	(1.722)	(1.650)	(2.306)
Group Mean	47.69	47.69	47.69	47.69	47.69
N Clusters	1992	1992	1992	1992	1991
Linear School Time Trends		X	X	X	X
Student Demographic Controls			X	X	X
Student G8 Test Controls				X	X
Grade 8 School-Cohort Fixed Effects					X
Proportion High-Achieving Students					

Standard errors are in parentheses and clustered at the school level. Coefficients are based on Equation (1). All models include cohort and school fixed effects. College graduation and wages include cohorts 2010–2014. Group Mean is the average for lower-income students in the sample. Student demographic controls include student own race, immigrant status and gender. Student grade 8 test controls include her grade 8 math and reading scores and an indicator for missing grade 8 math and reading tests.

Table A27: Impact of Proportion Upper-Income Controlling for the Proportion High-Achieving Students on Lower-Income Students' College Enrollment and wages: Robustness to Specification

	Model 1	Model 2	Model 3	Model 4	Model 5
Enrolled in College/University					
Proportion Upper-Income	0.0876	0.0522	0.0561	0.0642	0.0648
	(0.0241)	(0.0247)	(0.0244)	(0.0249)	(0.0305)
Group Mean	0.380	0.380	0.380	0.380	0.380
N Clusters	2141	2141	2141	2141	2141
Enrolled in a Public 2yr College					
Proportion Upper-Income	0.0927	0.0446	0.0471	0.0518	0.0200
	(0.0258)	(0.0253)	(0.0251)	(0.0253)	(0.0316)
Group Mean	0.290	0.290	0.290	0.290	0.290
N Clusters	2141	2141	2141	2141	2141
Enrolled in a Public 4yr College					
Proportion Upper-Income	0.0395	0.0404	0.0420	0.0481	0.0737
	(0.0159)	(0.0187)	(0.0186)	(0.0194)	(0.0228)
Group Mean	0.140	0.140	0.140	0.140	0.140
N Clusters	2141	2141	2141	2141	2141
Average Quarterly Wage 2022					
Proportion Upper-Income	566.5	979.9	978.7	893.4	684.8
	(343.1)	(412.8)	(412.2)	(401.6)	(624.0)
Group Mean	4307.2	4307.2	4307.2	4307.2	4307.2
N Clusters	1992	1992	1992	1992	1991
Income Percentile 2022					
Proportion Upper-Income	1.669	4.026	4.056	3.727	2.168
	(1.468)	(1.729)	(1.731)	(1.665)	(2.337)
Group Mean	47.69	47.69	47.69	47.69	47.69
N Clusters	1992	1992	1992	1992	1991
Linear School Time Trends		X	X	X	X
Student Demographic Controls			X	X	X
Student G8 Test Controls				X	X
Grade 8 School-Cohort Fixed Effects					X
Proportion High-Achieving Students	X	X	X	X	X

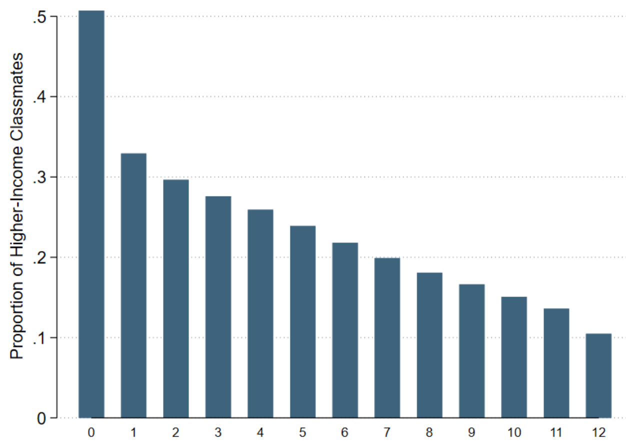
Similar to Table A26 but controlling for peer achievement as well based on average proportion high-achieving students based on distribution of grade 8 reading test-scores (excluding self).

Figure A1: Exposure to Higher-Income students is Defined by Parental Income Reported in their Financial Aid Application

pics/prop_upperincome_byFADLI.png

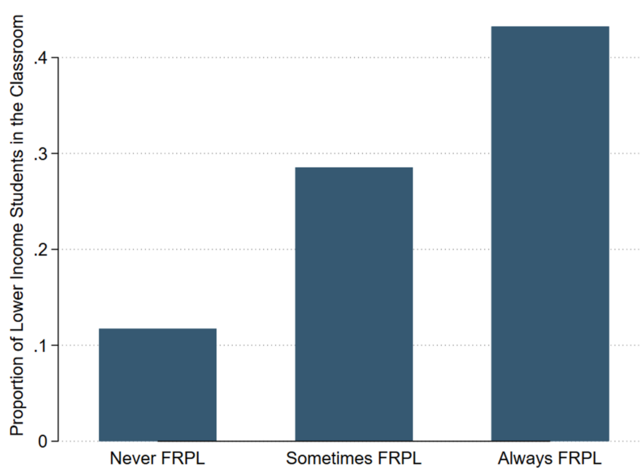
Notes: Parental income is based on parental gross adjusted income listed on the financial aid application. There may be students with parental income equivalent to this or higher but who have not applied for financial aid. Exposure to higher-income students is calculated by dividing the total number a student's classmates between grades 5 and 12 with parental income in the top 24 percentiles based on the distribution of parental income in the financial aid data is divided by the total number of classmates with financial aid data. Lower- middle- and upper-income students on the x-axis are defined by proportion of years in free/reduced lunch status.

Figure A2: Exposure to Higher-Income Peers Decreases with Number of Years on Free/Reduced Lunch



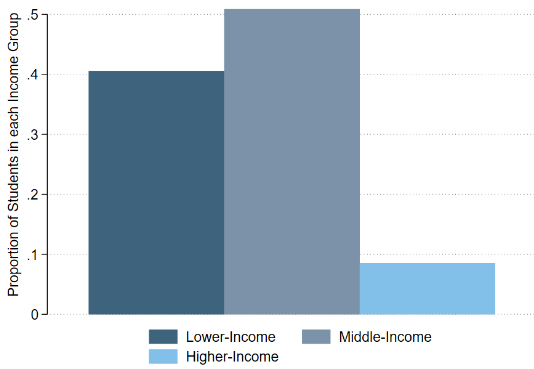
Notes: The X-axis captures years on free/reduced lunch. Years on free/reduced lunch depends on students' free/reduced price lunch status in each of the sixteen years I observe them in the data. I do not observe most students for more than thirteen years, and thus, I cap the number of years on free/reduced price lunch status at twelve. Twelve years includes students who are observed for 12 or more years on free/reduced price lunch. Exposure to higher-income peers is the proportion of total classmates between grades five to twelve that are higher income.

Figure A3: Proportion of Lower-Income Students in the Classroom: by Income Group

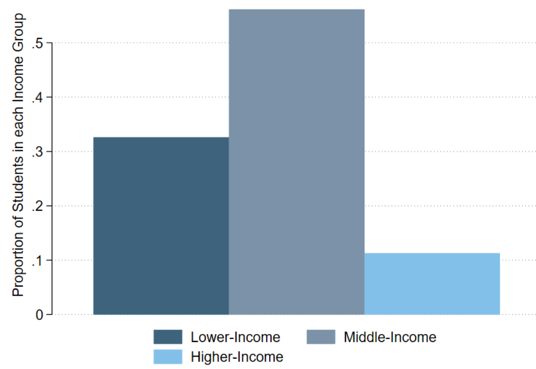


Notes: lower-income students are defined as students always on free/reduced lunch.

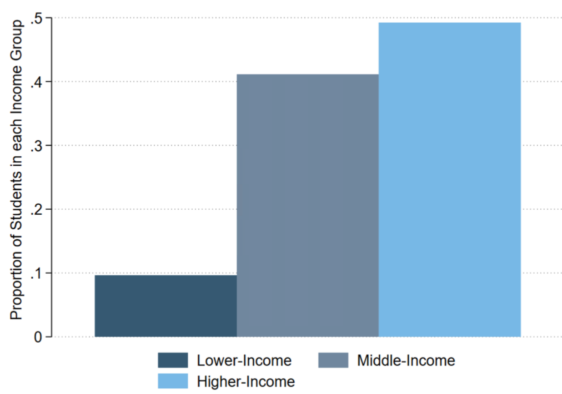
Figure A4: Distribution of Parental Income by Race/Ethnicity



(a) Hispanic Students



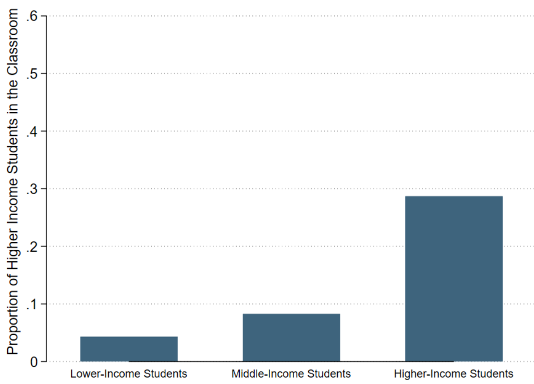
(b) Black Students



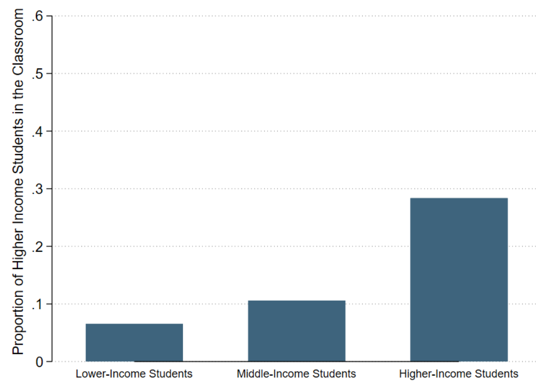
(c) White Students

Notes: This plot captures the average proportion of students in each income level, for each racial/ethnic group across three cohorts. The average is weighted by the number of students across three cohorts in each racial/ethnic group.

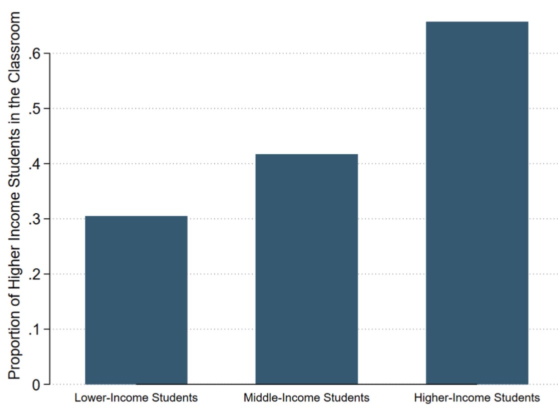
Figure A5: Proportion of Higher-Income, Same-Race/Ethnicity Classmates



(a) Hispanic Students



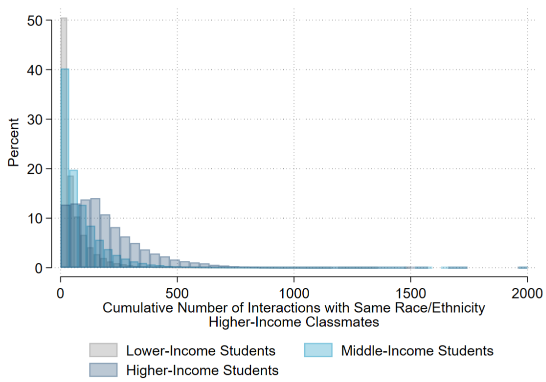
(b) Black Students



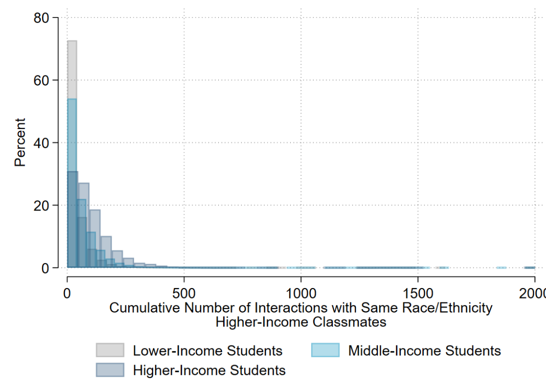
(c) White Students

Notes: These plots capture the proportion of higher-income classmates of the same race/ethnicity across grades 5 to 12 for each income and racial/ethnic group. The average is weighted by the number of students across three cohorts in each racial/ethnic group.

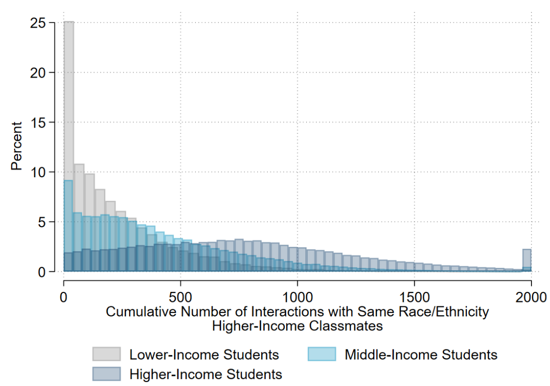
Figure A6: Cumulative Number of Higher-Income Same-Race/Ethnicity Classmates



(a) Hispanic Students



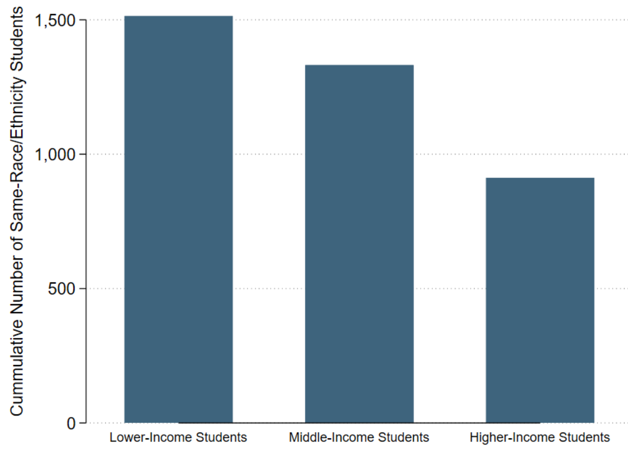
(b) Black Students



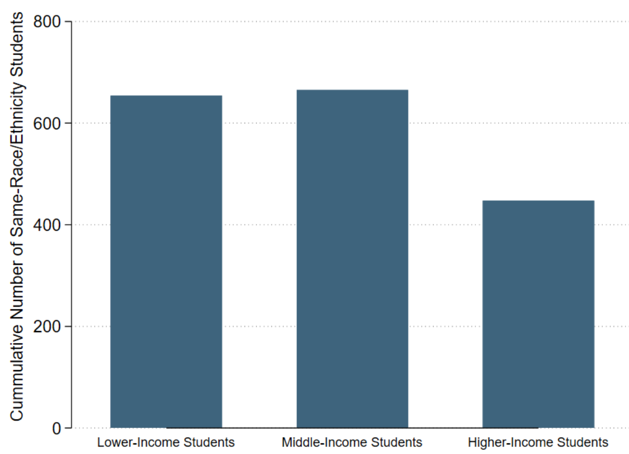
(c) White Students

Notes: Higher-income students are defined as students never on free/reduced lunch. These plots capture the percentage of students in each income group with various cumulative interactions with higher-income students. Outlier observations with more than 2000 interactions with higher-income classmates of the same race/ethnicity are top-coded. Every time a student is in a classroom with a higher-income student, it is counted as one interaction.

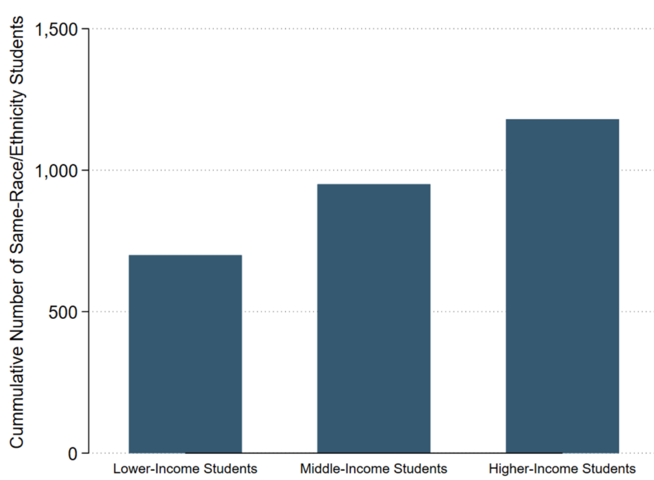
Figure A7: Cumulative Average Number of Same-Race/Ethnicity Classmates



(a) Hispanic Students



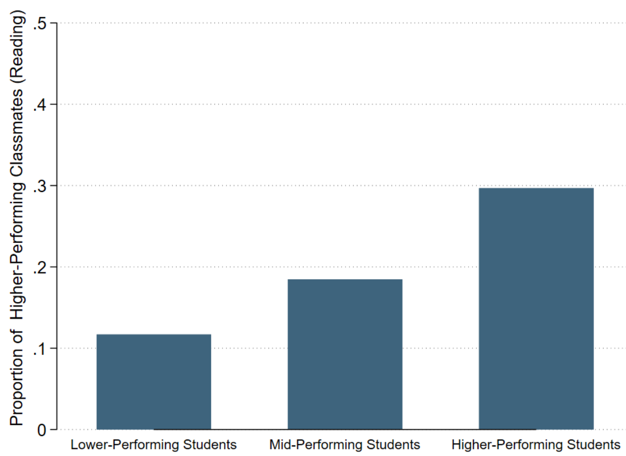
(b) Black Students



(c) White Students

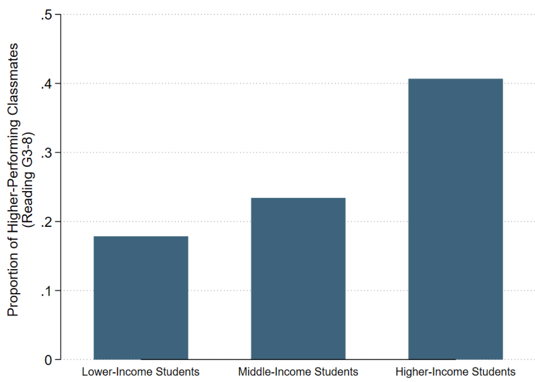
Notes: Higher-income students are defined as students never on free/reduced lunch. Each plot presents the average number of students of the same race/ethnicity a student is likely to interact with across grades 5 to 12.

Figure A8: The Cross-Test-Score Exposure Gap is Smaller than the Cross-Income Exposure Gap

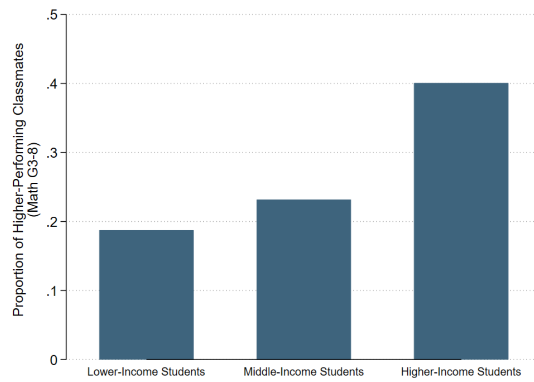


*Notes:*This plot captures students' cumulative proportion of higher-performing classmates between grade 5 and expected grade 12. I define higher-performing students as students who performed in the top 24 percentiles of the test score based on the grade 4 standardized reading test. The test score is standardized based on the raw score for all students who have taken the test in a given year. The percentile is based on the distribution of students who have a grade 4 test score. Approximately 5% of students are missing grade 4 reading test scores. I impute students' missing test score with 0 (i.e., the average test-score because the test score is standardized). Lower-achieving students are those who performed in the bottom 29 percentiles of grade 4 test scores.

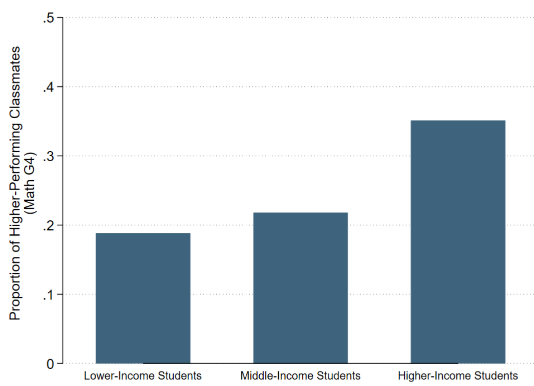
Figure A9: Sensitive to Choice of Test: Measure of Exposure to Higher-Achieving Students



(a) Average Grades 3 to 8 Reading Test



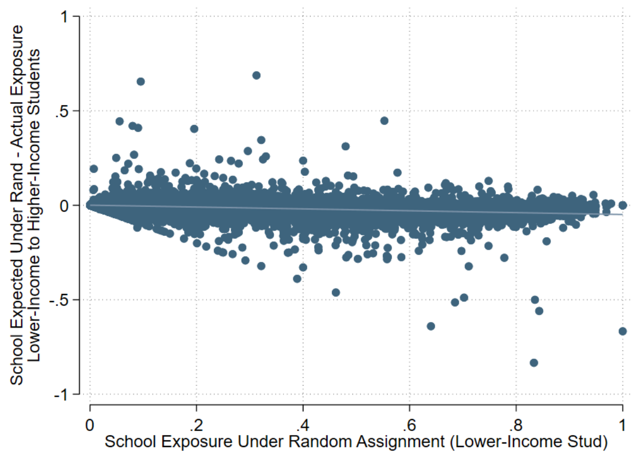
(b) Average Grades 3 to 8 Math Test



(c) Math G4 Test

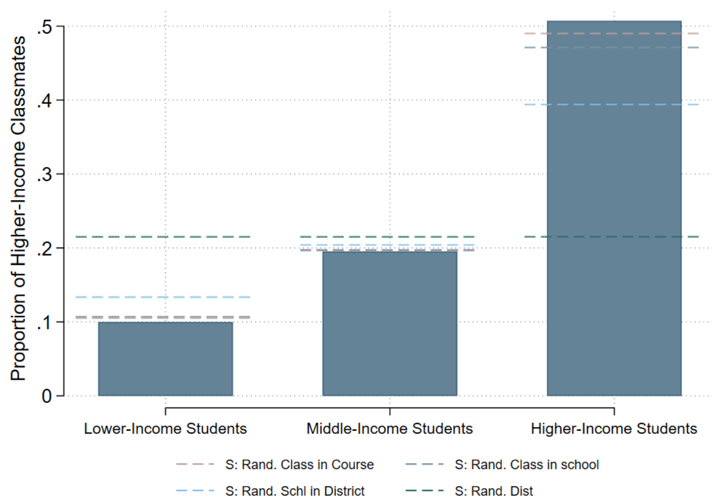
Notes: Plots capture the average cumulative proportion of total classmates that are higher-achieving by student income. All tests are standardized within year-grade. High achieving students are those who are in the top 24 percentiles of the average grades 3 to 8 standardized tests (or grade 4 test in panel (c)). Cumulative exposure based on following three cohorts of grade 5 students (2012-2014) to expected grade 12.

Figure A10: Relationship Between the Gap in Exposure and Potential Exposure Under Random Assignment



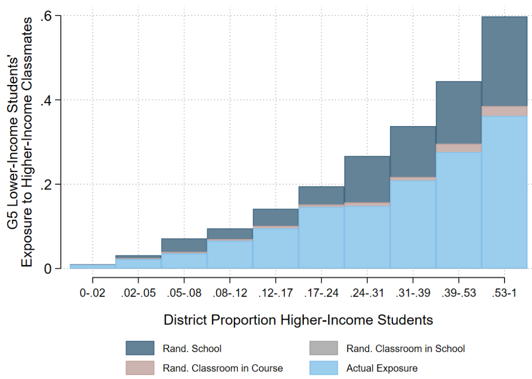
Notes: The scatter plot is at the cohort-year-school level. On the x-axis is the potential exposure to higher-income students under random assignment to classrooms within a school. This is on average equal to the proportion of higher-income students in the school. The y-axis is the difference between actual exposure to higher-income students and expected exposure had students been randomly assigned to classrooms. A larger value means that lower-income students are less likely to be exposed to higher-income students than we would have expected under random assignment to classrooms.

Figure A11: Exposure to Higher-Income Students: Observed Relative to Random Assignment

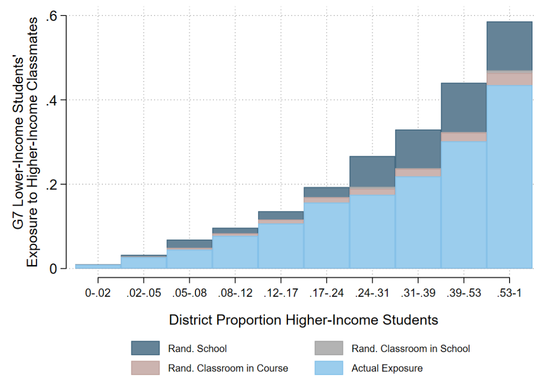


Notes: Higher-income students are defined as students never on free/reduced lunch. The bars capture the cumulative proportion of classmates that are higher-income calculated as the total number of higher-income students a given student is in a classroom with from grade 5 to expected grade 12 (excluding own status) divided by the total number of students in each classroom from grade 5 to expected grade 12 (excluding self). The average exposure is weighted by the number of students in each group. The dashed lines capture the various integration benchmarks. The "S: Rand. Dist" lines capture the expected proportion of higher-income classmates had students been randomly assigned to districts in each year-cohort: district integration benchmark. The "S: Rand Schl in District" lines capture the expected proportion of higher-income classmates had students been randomly assigned to schools within a district in each year-cohort (holding constant district composition): school integration benchmark. The "S: Rand Class in School" lines capture the expected proportion of higher-income classmates had students been randomly assigned to classrooms within a school in each year-cohort (holding constant school composition): classroom integration benchmark. The "S: Rand Class in Course" lines capture the expected proportion of higher-income classmates had students been randomly assigned to classrooms within a school in each year-cohort (holding constant school-course composition).

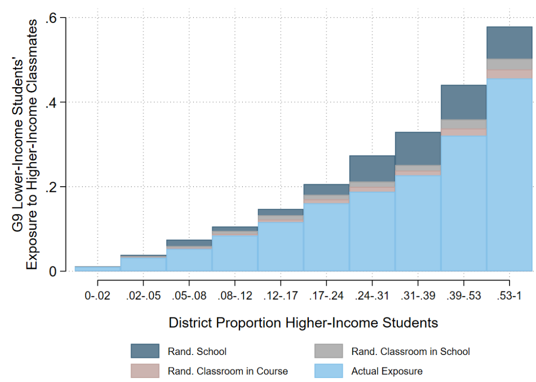
Figure A12: Choice of Course Accounts for More of the Gap in Exposure in Grade 9 than in Earlier Grades



(a) Grade 5



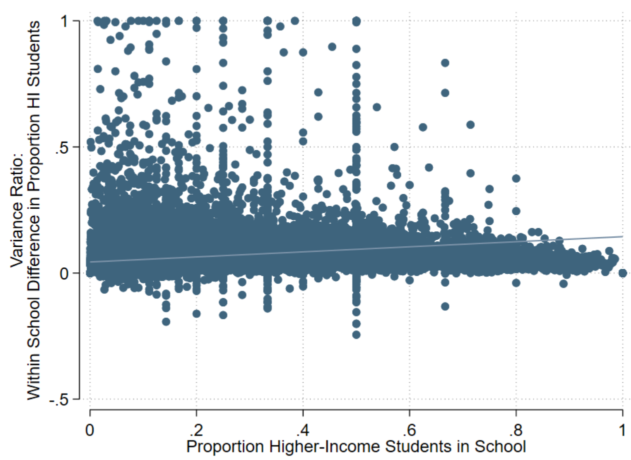
(b) Grade 7



(c) Grade 9

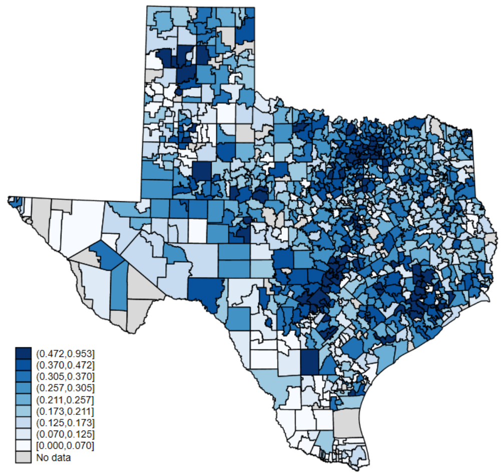
Notes: This plot presents lower-income students' exposure to higher-income students in districts with various proportions of higher-income students. Exposure is defined as the average proportion of higher-income classmates in a year. The light blue bar shows the observed proportion of higher-income students in lower-income students' classrooms. The navy bar presents the expected proportion of higher-income students had students been randomly assigned to schools in the district: school integration benchmark. The gray bar presents the expected proportion of higher-income students had students been randomly assigned to classrooms in the school: classroom integration benchmark. The pink bar presents the expected proportion of higher-income students had students been randomly assigned to classrooms in a course in a school. Districts are split into ten percentiles based on the distribution of the proportion of higher-income students in the district in a given school-year. The distribution is weighted by the number of students in each district (independent of income status). The lower and upper bound for each of the percentiles is shown on the x-axis. The panels present the gap by expected grade.

Figure A13: Correlation between the School Variance Ratio and Proportion of Higher Income Students in the School

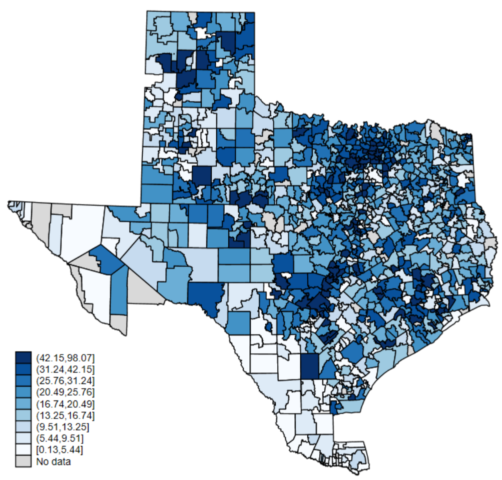


Notes: The y-axis captures the difference in the proportion of higher-income students in higher- relative to other-income student classrooms. The x-axis presents the proportion of higher-income students in the school across cohorts.

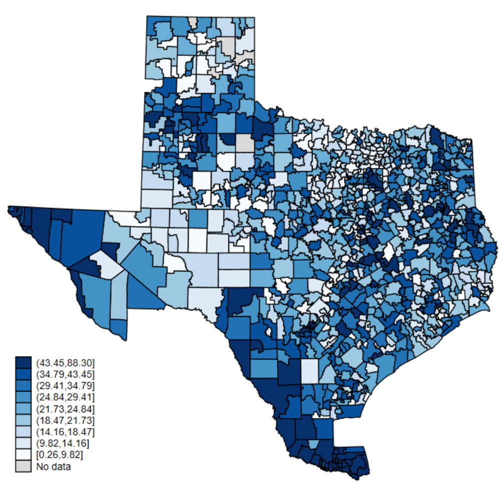
Figure A14: Percentage of Higher- and Lower-Income students



(a) Percentage of LI Students' Classmates that are Higher-Income



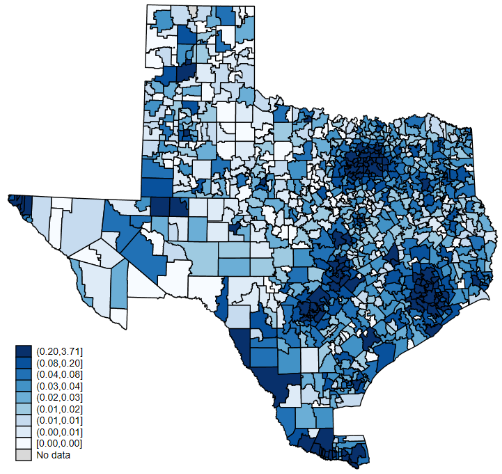
(b) Percentage of Students that are Higher-Income



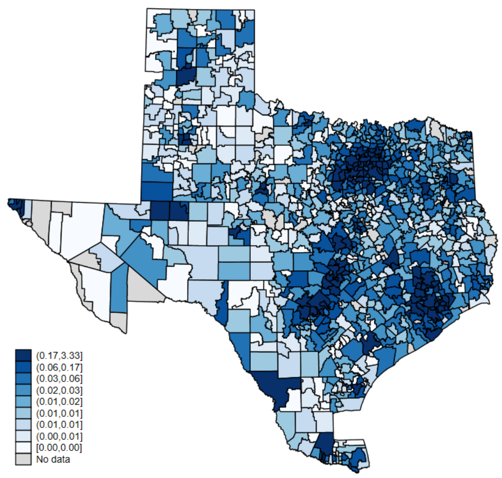
(c) Percentage of Students that are Lower-Income

Notes: The map in Panel (a) captures the percent of classmates in lower-income students' classrooms. The map in Panel (b) captures the percentage of students in each district that are higher income. Panel (c) captures the percentage of students that are lower income. In Panels (b) and (c), areas with fewer than 10 students in the numerator are shaded in grey under the "No-data" category. In Panel (a), areas with fewer than 10 higher- or lower-income students are shaded in grey under the "No-data" category.

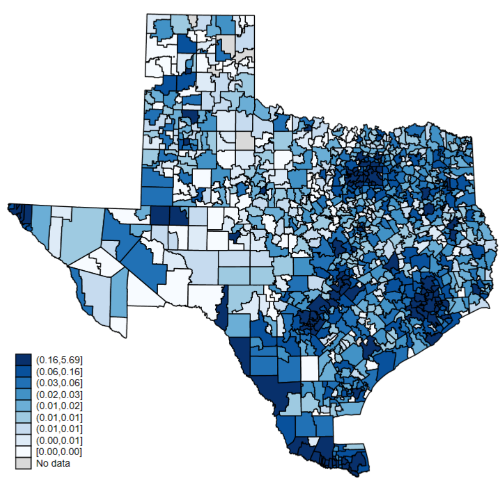
Figure A15: Percentage of Population in Each District



(a) Percentage of Total Student Population



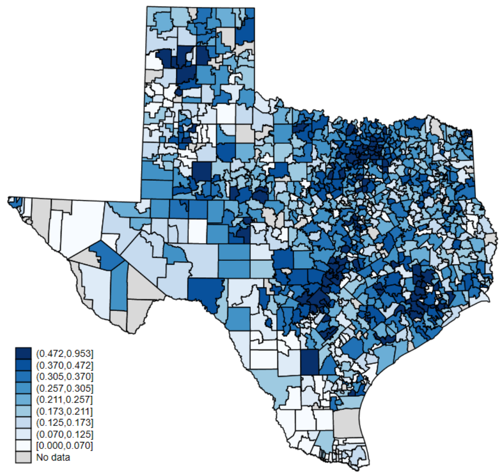
(b) Percentage of Total Higher-Income student Population



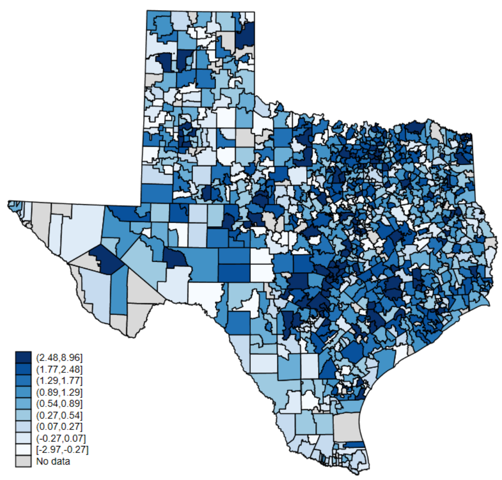
(c) Percentage of Total Lower-Income student Population

Notes: Panel (a) captures the percentage of the total student population residing in each district. Panel (b) captures the percentage of the total higher-income student population residing in each district. Panel (c) captures the percentage of the total lower-income student population residing in each district. Areas with fewer than 10 students are shaded in grey under the "No-data" category.

Figure A16: Observed Exposure Relative to Exposure Under Random Assignment



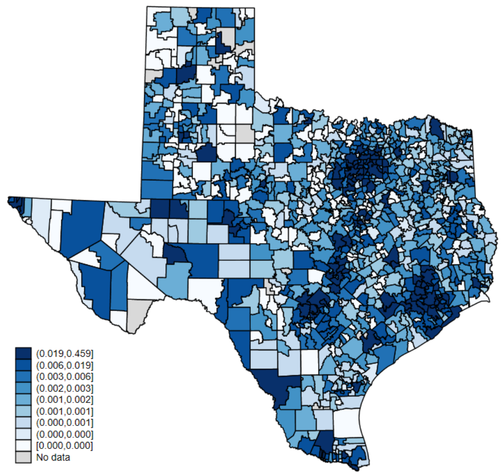
(a) Relative to Random Assignment to Schools and Classrooms within Districts



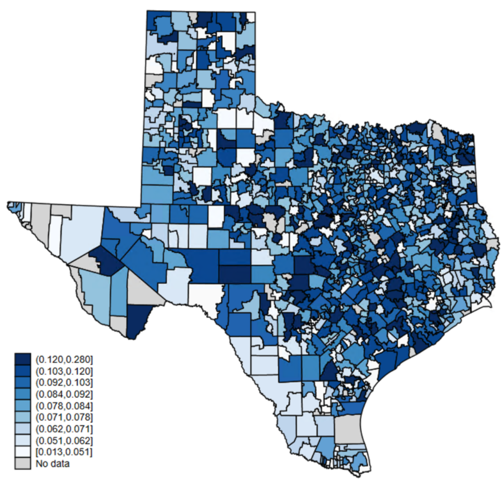
(b) Relative to Random Assignment to Classrooms within Schools

Notes: This plot is limited to lower-income students. Lower-income students are students always on free/reduced lunch. The units used are percentages. The plot captures the percentage-point difference between the observed proportion of higher-income students to whom lower-income students are exposed and the expected proportion of higher-income students had students been randomly assigned to classrooms within the district. The maps are constructed by grouping school districts into 9 deciles and shading the areas so that lighter colors correspond to lower difference in observed and simulated exposure. Areas with fewer than 10 higher- or lower-income students are shaded in grey under the "No-data" category. Figure (a) captures the percentage-point difference between the observed proportion of higher-income students to whom lower-income students are exposed and the expected proportion of higher-income students had students been randomly assigned to schools and classrooms within the district. Figure (b) captures the percentage point difference between the observed proportion of higher-income students to whom lower-income students are exposed and the expected proportion of higher-income students had students been randomly assigned to classrooms within the district.

Figure A17: Level of Sorting by Income Within and Between Schools in a District



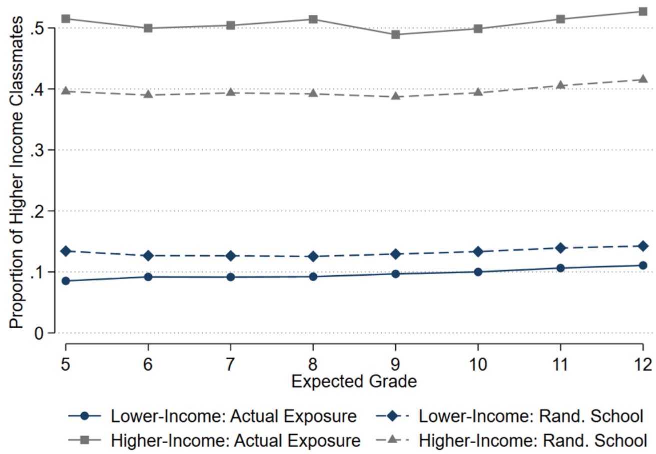
(a) Variance Ratio between Schools



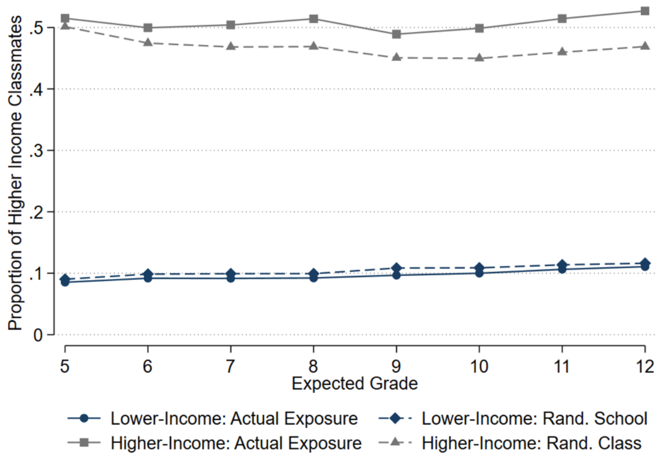
(b) Variance Ratio within Schools

Notes: Panel (a) captures within-district sorting across schools by income. It is the difference in the proportion of higher-income students in higher- relative to other-income student schools, within the same district. Panel (b) captures within-school sorting across classrooms. The line of best fit is weighted by the number of students enrolled across cohorts in each expected grade level. It is the difference in the proportion of higher-income students in higher-relative to other-income student classrooms, within the same school.

Figure A18: The Exposure Gap between Random School Assignment and Observed is Consistent Across Grades but Increases under Random Classroom Assignment



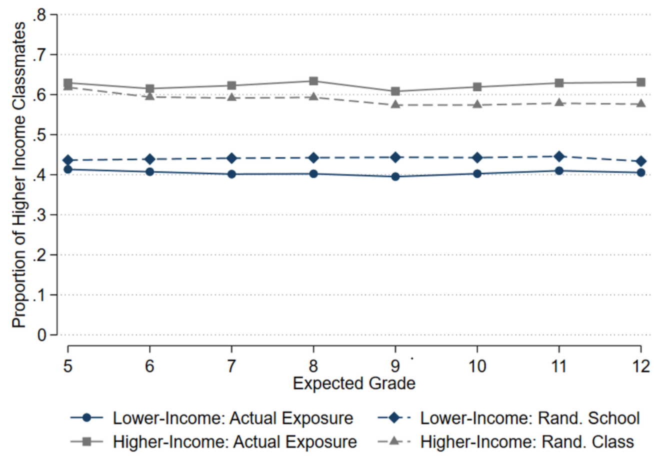
(a) Random Assignment to Schools and Classrooms within District



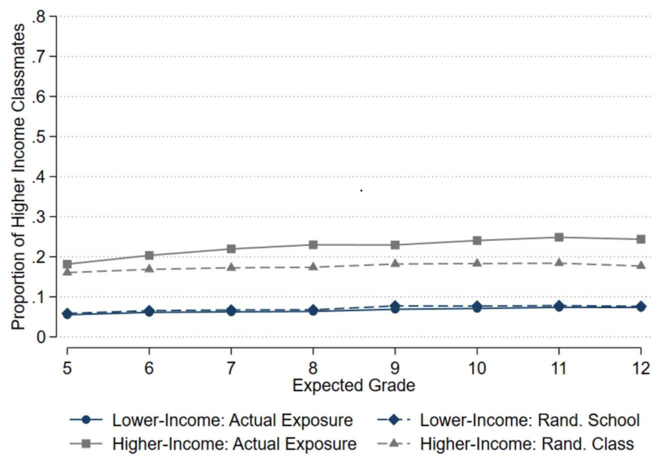
(b) Random Assignment to Classrooms within School

Notes: Higher-income students are defined as students never on free/reduced lunch. The solid lines in both plots capture exposure to higher-income students in each grade. Exposure is defined as the proportion of a student's classmates that are higher income. Expected grade is based on what year it is and when I first observe a cohort of students in grade 5. The average exposure is based on the number of students across cohorts enrolled in an expected grade. In Panel (a), the dashed lines capture the average proportion of higher-income students had students been randomly assigned to schools and classrooms in a district each year. In Panel (b), the dashed lines capture the average proportion of higher-income students had students been randomly assigned to classrooms in a school each year.

Figure A19: Classroom Sorting Matters for Lower-Income Students in Schools with a Large Proportion of Higher-Income Students



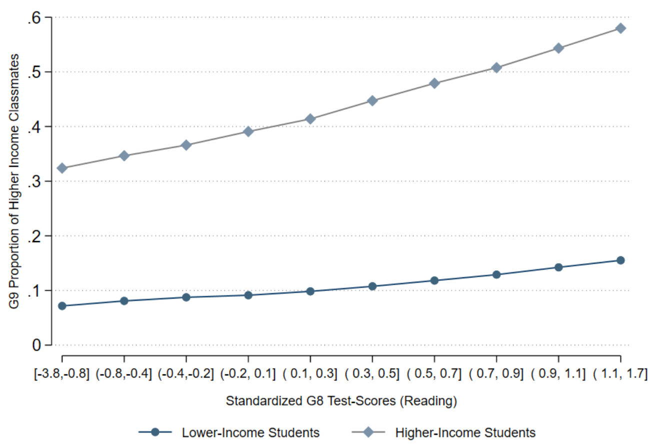
(a) Higher-Income Schools



(b) Lower-Income Schools

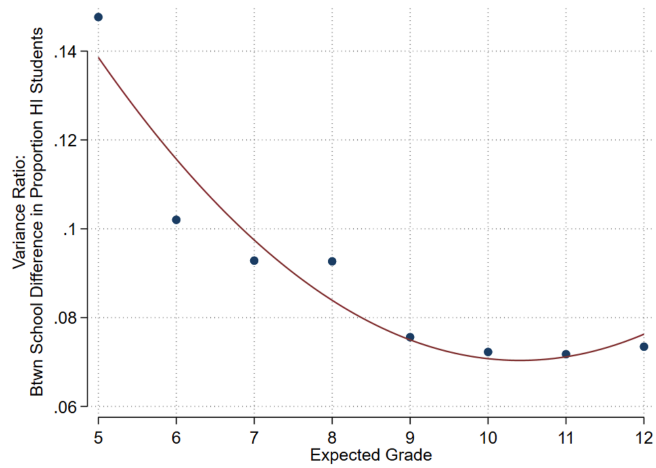
Notes: Higher-Income schools are schools that are in the top 70th percentile of schools in terms of the proportion of higher-income students they serve. Those are schools that serve 30% or more higher-income students. The dashed lines in both plots capture the average proportion of higher-income students had students been randomly assigned to classrooms in a school each year. The solid lines in both plots capture exposure to higher-income students in each grade. Exposure is defined as the proportion of a student's classmates that are higher income. Expected grade is based on what year it is and when I first observe a cohort of students in grade 5. The average exposure is based on the number of students across cohorts enrolled in a expected grade.

Figure A20: Gap in Exposure to Higher-Income Students Exists Independent of Academic Performance

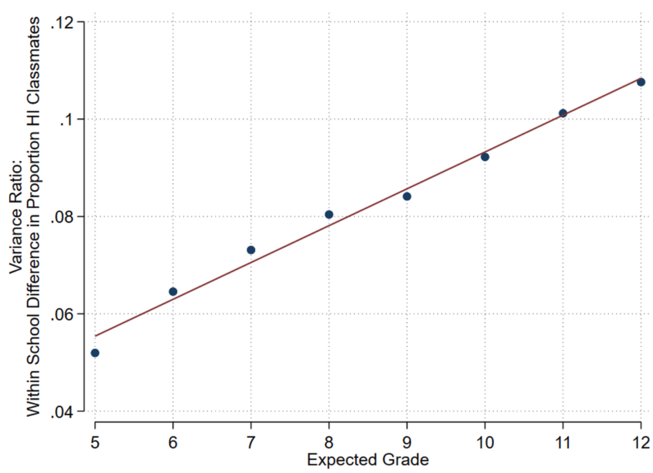


Notes: The y-axis captures students' average exposure to higher-income classmates (excluding own status) in expected grade 9 in each bin. Student test score is based on the grade 8 reading test, standardized based on the full sample of students who have taken the test in a given year. The plot excludes students without test scores (7% of the sample of students are missing grade 8 reading test scores). Students are split into 10 percentiles based on their test score in grade 8. The range of standardized test scores included in each percentile is presented on the x-axis.

Figure A21: Sorting between Schools Decreases as Within-School Sorting Increases Linearly with Every Grade



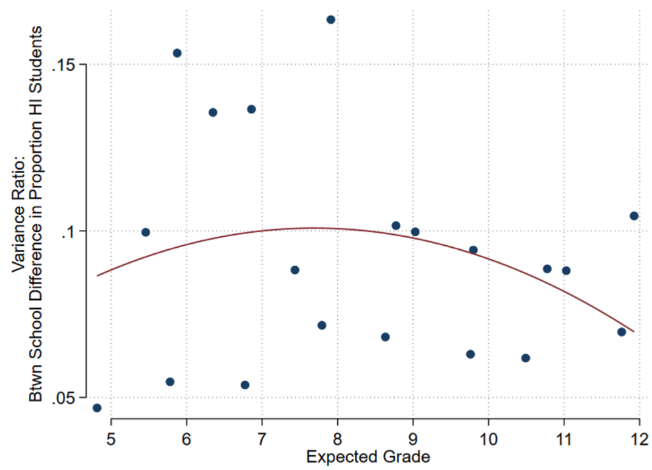
(a) Within District, Difference in School Proportion of Higher-Income Students



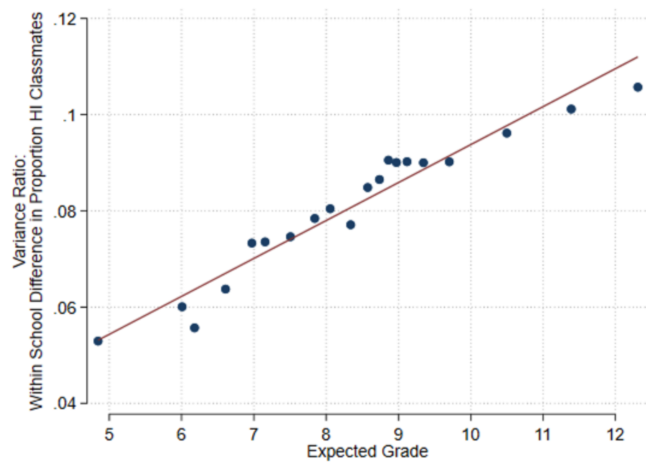
(b) Within School, Difference in Classroom Proportion of Higher-Income Students

Notes: Panel (a) captures the relationship between within-district sorting across schools and grade level. Panel (b) captures the relationship between within-school sorting across classrooms and grade level. The line of best fit is weighted by the number of students enrolled across cohorts in each expected grade level. Bins are based on grouping the x-values into 20 equal-sized bins. It then computes the average y-variable value for each bin.

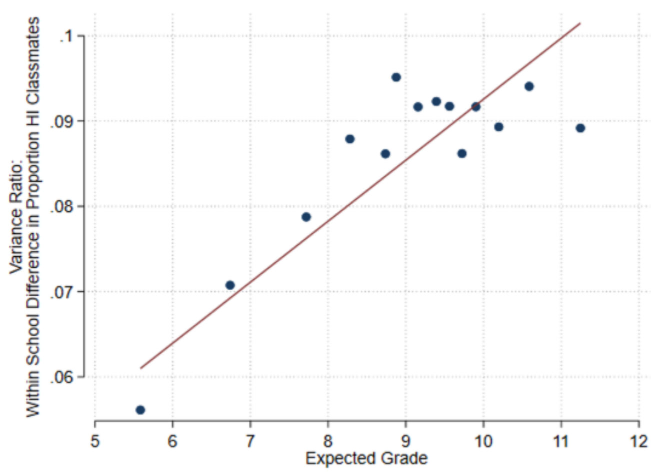
Figure A22: Change in Sorting between Schools is Mainly Driven by the Change in the Number of School Options



(a) Within District, Difference in Proportion of HI Students in School: Conditional on School-to-Students



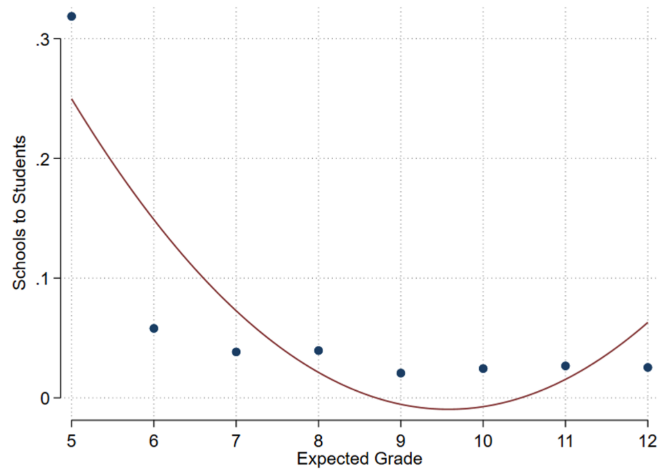
(b) Within School, Difference in Proportion of HI Students in Classroom: Conditional on Classroom-to-Students



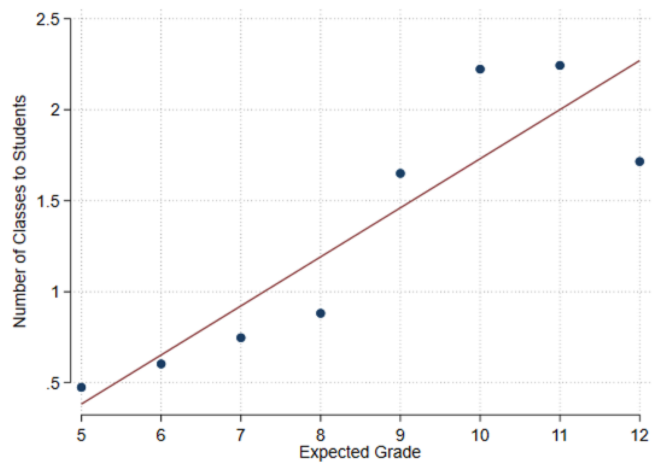
(c) Within School, Difference in Proportion of HI Students in Classroom: Conditional on Advanced Courses-to-Students

Notes: Panel (a) captures the relationship between within-district sorting across schools and grade level, with controls for the number of schools serving that grade level in a district to the number of students enrolled in that grade level. Panels (b) and (c) capture the relationship between within-school sorting across classrooms and grade level. In Panel (b), I control for the number of classrooms to students offered in a school at a grade level. In Panel (c), I control for the number of advanced courses offered in a grade level in a school. Note that courses are labeled as advanced only at the high school level. The line of best fit is weighted by the number of students enrolled across cohorts in each expected grade level. Bins are based on grouping the x-values into 20 equal-sized bins. It then computes the average y-variable value for each bin.

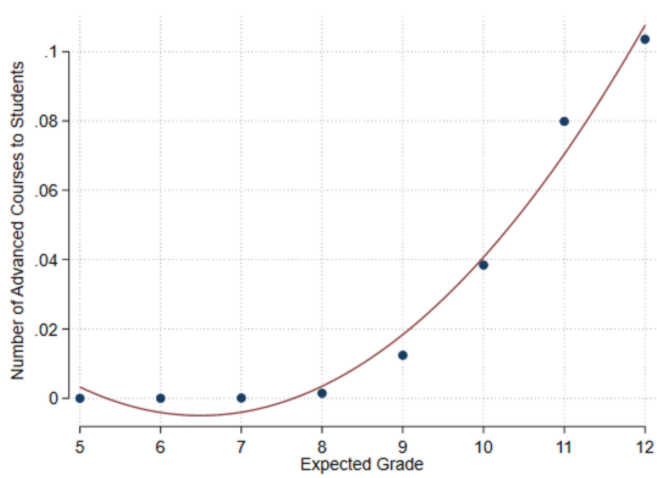
Figure A23: Changes in School- and Class-to-Student Ratio Across Grades



(a) School-to-Student Ratio Across Grades



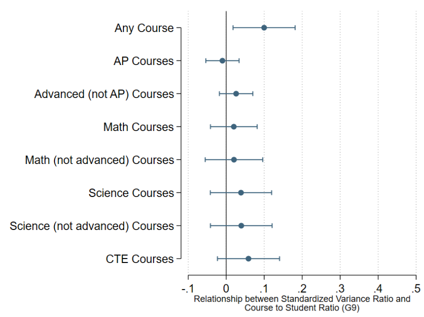
(b) Classroom-to-Student Ratio Across Grades



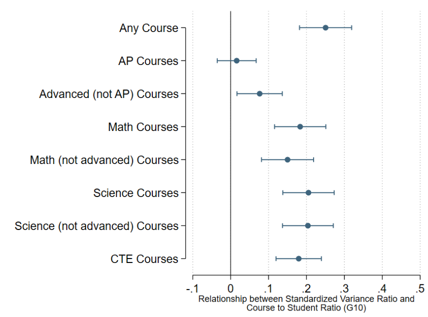
(c) Advanced Courses-to-Student Ratio Across Grades

Notes: Panel (a) captures the average number of schools to students in each grade level. Panel (b) captures the average number of classrooms to students in each grade level. Panel (c) captures the average number of advanced courses to students in each grade level. Note that courses are identified as advanced in the TEA data starting in high school.

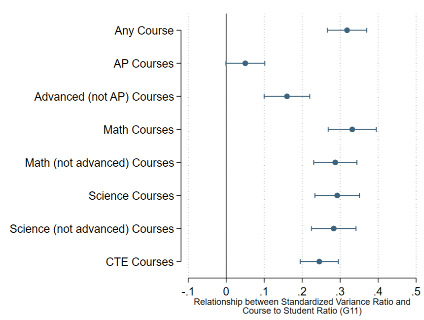
Figure A24: Type and Number of Courses Offered Seem to Account for More of the Variation in Sorting in Later High School Grades



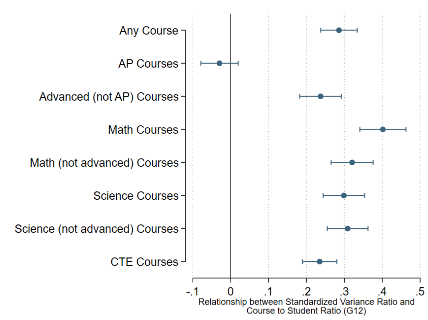
(a) Grade 9



(b) Grade 10



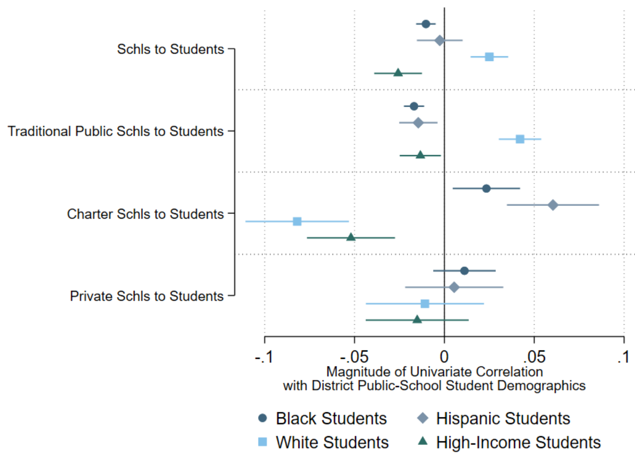
(c) Grade 11



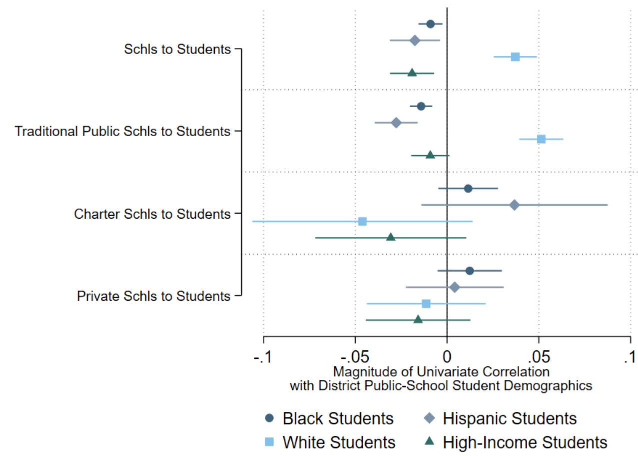
(d) Grade 12

Notes: Based on 2019 high school classroom enrollment data. School-level univariate regression coefficients from regressing the standardized sorting measure on the number of courses offered to students served are presented standardized in the first row. The other rows capture the correlation with other specific groups of courses to students served. Math courses capture the number of any math course to number of students served, standardized. Math (not advanced) courses capture all math courses that are not advanced to the number of students served. The standardization is based on the weighted distribution of courses to students and level of within-school sorting in each grade across schools. The correlation is weighted by the number of students enrolled in a school in a given grade. The 95% confidence intervals are presented. The standard errors are clustered at the school level.

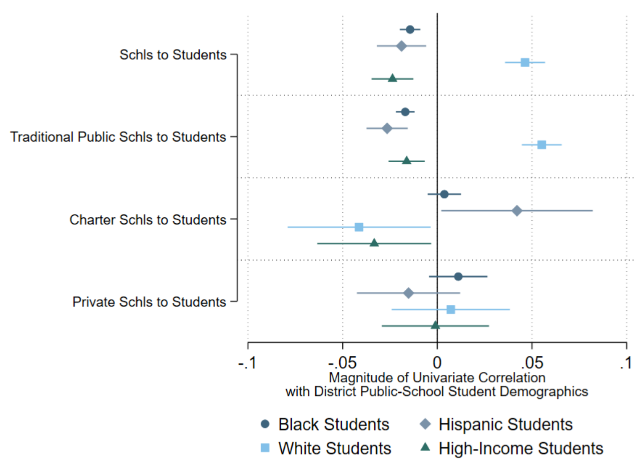
Figure A25: District Demographics and School Offerings



(a) Grade 3 to 5



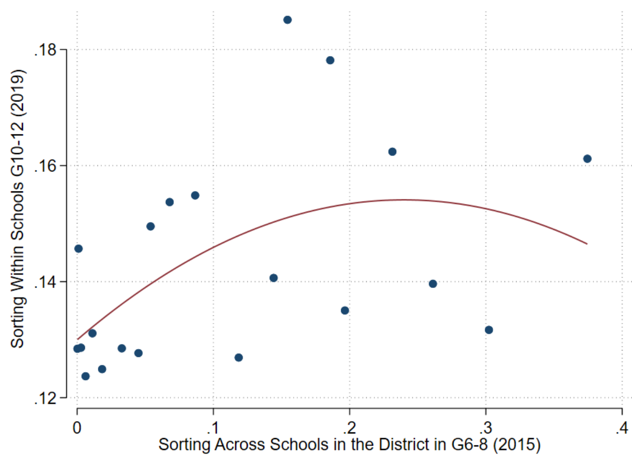
(b) Grades 6 to 8



(c) Grades 9 to 12

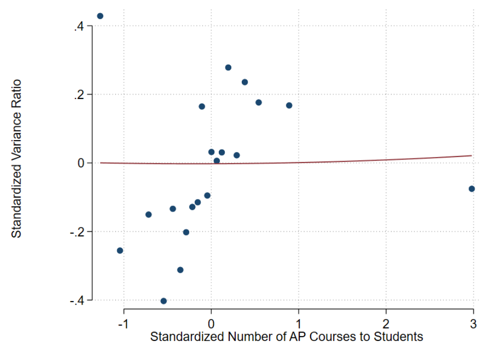
Notes: The number of schools to students is standardized – a one-unit increase is a one-standard-deviation increase in the number of schools to students. Schools are placed into districts, and the ratio is calculated as the number of schools in the district to the number of students served in the district in 2019. The number of private schools and students served in these schools is estimated based on a list of private schools and the number of students and grades served by each school obtained from the Texas Alliances Accredited Private Commission's archive for the 2018–2019 school year. The estimates are based on regressing the proportion of a given demographic (e.g., proportion of Hispanic students) on the standardized number of schools to students in the county.

Figure A26: The Level of Between-School Sorting in Middle School Does not Seem to Matter for Within-School Sorting in High School

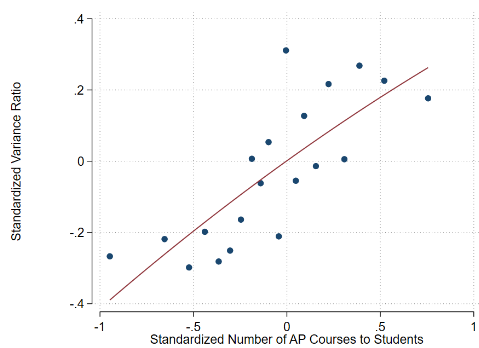


Notes: The x-axis captures between-school sorting in middle school in a given district. I use the variance ratio to capture between-school sorting in middle school in 2015. To calculate the between-school variance ratio, I calculate the proportion of higher-income students in the district and the proportion of higher-income students in middle schools in which higher-income students are enrolled. The variance ratio captures the average difference in the proportion of higher-income students in schools attended by higher- relative to other-income students. The y-axis captures within-school difference in the proportion of higher-income students in higher- relative to other-income student classrooms as captured by Equation (1). Of students in middle school in 2015, 78% are enrolled in the same district in 2019. The fitted line is based on weighting each school by the number of students enrolled in a school in high school. Bins are equal sizes, based on the number of observations divided by 20. Because charter schools are not assigned to a district, this plot excludes students enrolled in charter schools. This is a small number of students (approximately 5% of students).

Figure A27: Relationship between AP Courses to Students and Variance Ratio



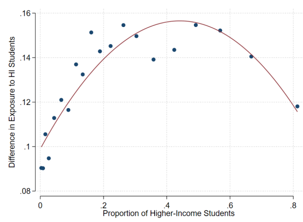
(a) Full Sample



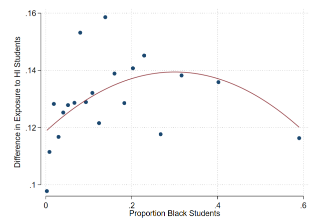
(b) Excluding above 1 standard deviation AP courses to students and schools with no AP course offered

Notes: Based on 2019 high school classroom enrollment data. Bins are based on grouping the x-values into 20 equal-sized bins. It then computes the average y-variable value for that bin. The fitted line is weighted by the number of high school students enrolled. Panel (a) plots the relationship between the number of AP courses to students and the full sample. Panel (b) limits the sample to schools offering at least one AP course and below 1 standard deviations in terms of the number of AP courses they offer to students.

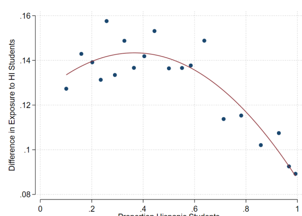
Figure A28: School Composition and Within-School Sorting by Income



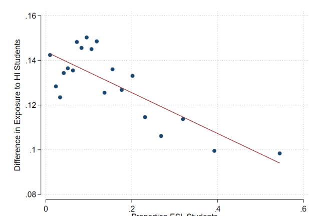
(a) Proportion of Higher-Income Students



(b) Proportion of Black Students



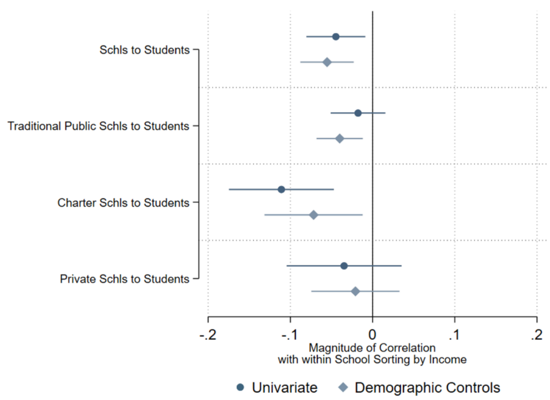
(c) Proportion of Hispanic Students



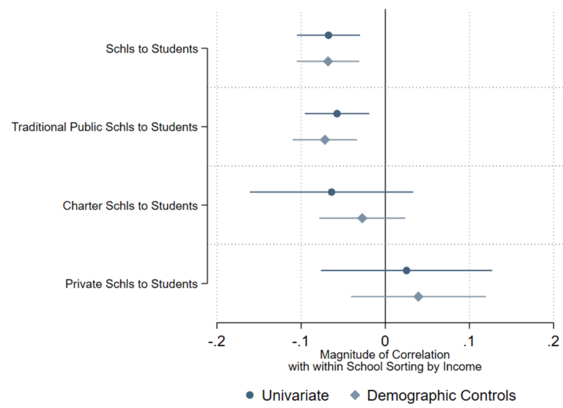
(d) Proportion of ESL Students

Notes: Based on 2019 high school classroom enrollment data. Panel (a) captures the relationship between the proportion of higher-income students and the within-school sorting. Panel (b) captures the relationship between the proportion of Black students and sorting. Panel (c) captures the relationship between the proportion of Latin-American students and sorting. Panel (d) captures the relationship between the proportion of students with an English as a Second Language designation and within-school sorting. Bins are based on grouping the x-values into 20 equal-sized bins. It then computes the average y-variable value for that bin. The fitted line is weighted by the number of high school students enrolled.

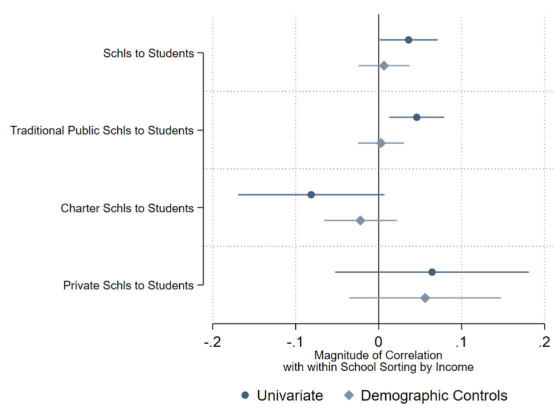
Figure A29: No Strong Evidence of an Association between Within-School Sorting in Public Schools and Number of School Options



(a) Grades 3 to 5



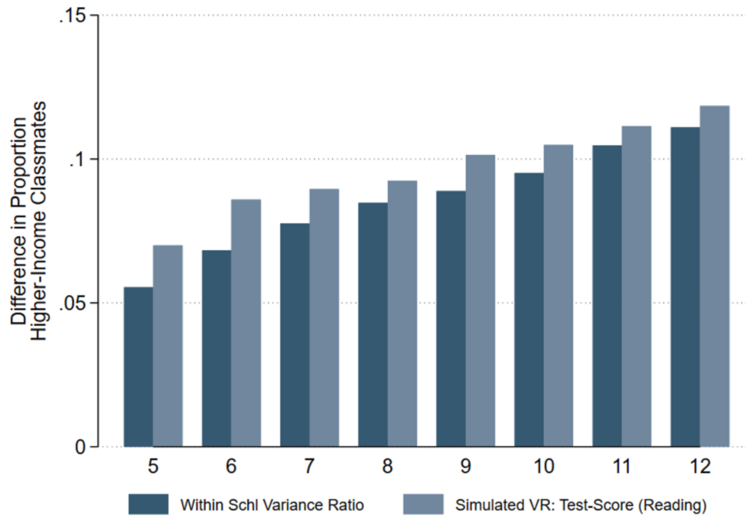
(b) Grades 6 to 8



(c) Grades 9 to 12

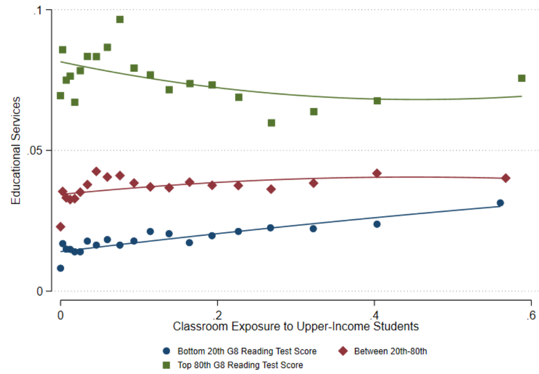
Notes: Similar to Figure 10 but with the within-school variance ratio (sorting) as the outcome.

Figure A30: Had Students Been Assigned to Classrooms by Test Score, the Gap in Exposure by Income Within Schools Would Have Been Slightly Larger

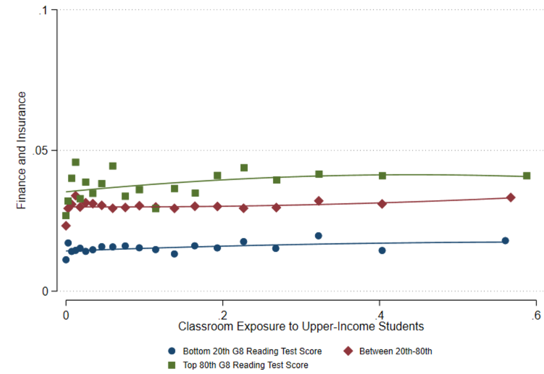


Notes: This plot captures the variance ratio (VR) under two settings. The Within Schl Variance Ratio bars capture the observed within-school variance ratio in every grade. The Simulated VR: Test Score bars capture the variance ratio under a simulation in which students in a school are ranked by grade 4 test score and then placed in classrooms by test score. I keep the number of classrooms and students assigned to a classroom the same as that observed in a given year. I run the simulation using students' grade 4 reading test scores. School grade levels that either do not have higher-income students or do not have other-income students are not included in the sample to focus on the role of test scores in schools with variation in income composition.

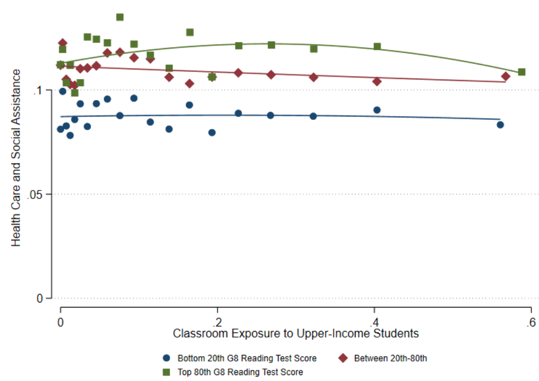
Figure A31: Exposure to Upper-Income Students and Industry of Employment



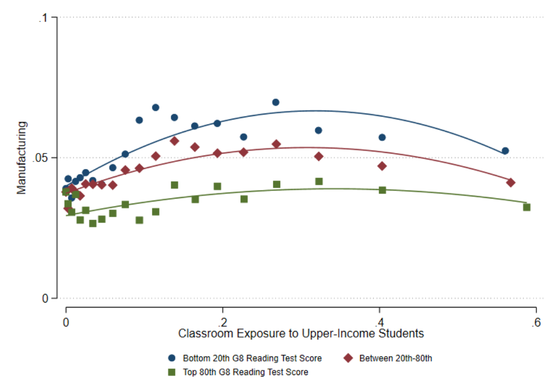
(a) Education



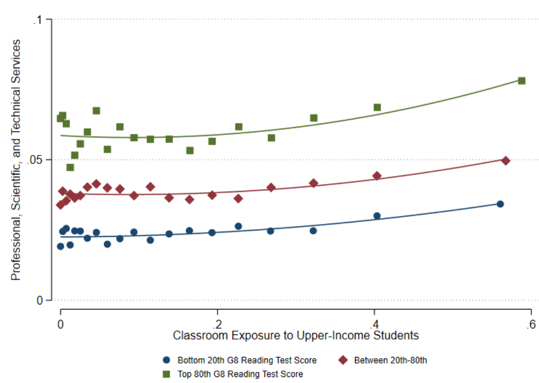
(b) Finance



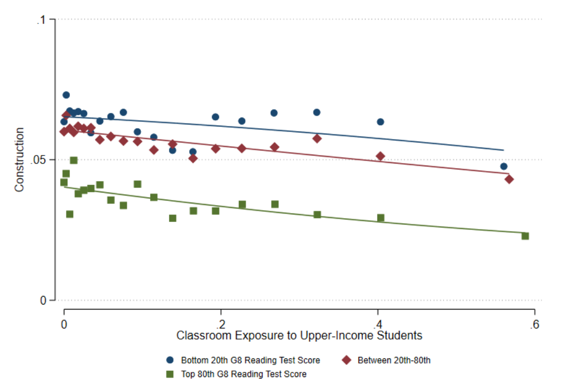
(c) Healthcare



(d) Manufacturing



(e) Professional Sciences



(f) Construction

Notes: The line and plots are similar to Figure (14). All outcomes include cohorts 2011 to 2014. The industry of employment is based on unemployment insurance data and does not identify the type of job within the industry.